DIRECT TESTIMONY OF
JOSEPH M. LYNCH, Ph.D.
ON BEHALF OF
DOMINION ENERGY SOUTH CAROLINA, INC.
DOCKET NO. 2019-226-E

Q. PLEASE STATE YOUR NAME AND BUSINESS ADDRESS.

A. My name is Joseph M. Lynch, and my business address is 220 Operation Way, Cayce, South Carolina.

Q. BY WHOM ARE YOU EMPLOYED AND IN WHAT CAPACITY?

A. I am employed by Dominion Energy South Carolina, Inc. ("DESC" or the "Company") as Manager of Resource Planning.

Q. PLEASE DESCRIBE YOUR DUTIES RELATED TO RESOURCE PLANNING IN YOUR CURRENT POSITION.

A. I am responsible for managing the department that produces DESC's forecast of energy, peak demand, and revenue. I also am responsible for overseeing the Company's load research program.

Q. DESCRIBE YOUR EDUCATIONAL BACKGROUND AND PROFESSIONAL EXPERIENCE.

A. I graduated from St. Francis College in Brooklyn, New York, with a Bachelor of Science degree in mathematics. From the University of South Carolina, I received a Master of Arts degree in mathematics, an MBA, and a Ph.D. in management science and finance. I was employed by the Company as Senior Budget Analyst in 1977 to develop econometric models to forecast sales and revenue. In 1980, I was promoted to Supervisor of the Load Research Department. In 1985, I became Supervisor of Regulatory Research, where I was responsible for load research and electric rate design. In 1989, I became Supervisor of Forecasting and Regulatory Research, and, in 1991, I was promoted to my current position of Manager of Resource Planning.

Q. HAVE YOU PREVIOUSLY TESTIFIED BEFORE THE PUBLIC SERVICE COMMISSION OF SOUTH CAROLINA ("COMMISSION")?

A. Yes. I have testified on numerous occasions before this Commission.

Q. WHAT IS THE PURPOSE OF YOUR TESTIMONY?

A. The purpose of my testimony is to discuss the energy and peak demand forecast and the forecast scenarios included in DESC's 2020 Integrated Resource Plan ("IRP") and the development of DESC's reserve margin policy.

DESC'S ENERGY FORECAST

Q. WHAT IS THE FORECASTING PROCESS USED AT DESC?

A. Every summer the forecast of customers, sales, peak demands and revenue is made essentially from scratch. Datasets are updated with the latest information through the beginning of the summer and the statistical models are re-run and checked for adequacy, with changes being made where improvements in the forecast can be identified. Additionally, the Large Customer Department and the Economic Development Department are asked to provide input regarding existing customer expansions or contractions and the possibility of new large customers being added to the system. The forecast is divided into two parts: the short run and the long run. The short run forecast is made by month for two years. The revenue projections derived from the short run forecast are critical to the Company's budgeting process and short run operations. The short run forecast is made at the rate level since the revenue projections need to be made. The long run forecast is made by year for the eighteen years beyond the two years covered in the short run. The long run forecast is critical to the long range planning of the Company.

Q. CAN YOU PROVIDE SOME DETAILS ON THE COMPONENTS OF DESC'S FORECASTING METHODOLOGY?

A. Yes. Exhibit No. __(JML-1) provides a description of the components used in both the short run and the long run models. As mentioned, the short run models involve many more components than the long run largely because of the need to incorporate rate level detail. For example, sales under Rate 8, the standard residential tariff, are broken down into single-family, multi-family and mobile home categories and are further divided into electric space heating and non-electric space heating customers with average use per customer split between summer models and winter models. The number of customers for each of these categories is projected separately. This translates into about 18 different statistical models just to forecast Rate 8 sales. Similar categories are formed for the other major residential rates *i.e.,* 1, 2 and 6. In the industrial class there are about 30 large customers who comprise about 70% of industrial sales. Sales to each of these customers are projected at the individual customer level.

Q. IS THE NATURE OF THE LONG RUN STATISTICAL MODELS DIFFERENT FROM THE SHORT RUN MODELS?

A. Yes. All the long run models project rates of growth for the different components of the forecast. Sales projected for the second year of the short run are summarized into over 30 separate components and these become the base year for the long run forecast. Each of these components has an associated long run statistical model that projects its growth path over the following eighteen years. While the long run forecast is less granular than the short run, it is still quite detailed, having more than 30 individual components. For example, in the residential class while the rate detail is collapsed, the breakout by single-family home, multi-family home and mobile home is retained as well as the split between electric space heating and non-electric space heating customers with the number of customers and the average use per customer projected separately. The long run industrial forecast of growth rates is not made for individual customers but rather at the 2-digit Standard Industrial Classification ("SIC") level.

Q. HOW DOES THE COMPANY VERIFY THAT THE ENERGY FORECAST IS REASONABLE?

A. The best way to gauge the reasonableness of the forecast is to compare the forecast with actual results. For example, the following table compares the projected growth over the next five years to that of the last five years. In the case of the residential and commercial classes, "Total Gigawatt Hour ("GWh") Sales" is projected to grow at about the same rate in the future as it did in the past. This suggests that the forecast in this case is at least reasonable. The growth in industrial sales shows the biggest difference between forecast and history. But this disparity can be explained. Over the last five years, two large customers became co-generators resulting in the loss of about 700 GWh in sales which, if added to the total sales in 2019, would produce a growth rate of about 0.5%.

Table 1

		Sales Data				% Growth	
Class	Item	_2014	_2019	_2020	_2025	History	Forecast
Residential	Nbr Customers	587,856	636,386	645,797	688,741	1.6	1.3
	kWh per Customer	13,167	12,843	12,623	12,410	-0.5	-0.3
	Total GWh Sales	7,741	8,173	8,152	8,547	1.1	1.0
Commercial	Nbr Customers	91,952	97,544	98,185	103,547	1.2	1.1
	kWh per Customer	79,116	75,137	75,134	70,929	-1.0	-1.1
	Total GWh Sales	7,275	7,329	7,377	7,344	0.1	-0.1
Industrial	Total GWh Sales	6,234	5,694	5,812	6,090	-1.8	0.9
All_Sales	Total GWh Sales	22,769	22,661	22,952	23,104	-0.1	0.1

The following table compares the growth rates projected over the next 15 years to that experienced over the past 15 years. The decline in the average use per customer in the residential class is expected to level off. It had been decreasing since the Great Recession of 2007,[1] but we believe it will level off in the near future. The average use per customer in the commercial class is projected to continue decreasing, but this is a function of the mix of customers. Fewer large commercial customers are projected than smaller, which lowers the average use per customer for the whole class. Industrial sales are projected to grow slightly compared to a history of negative growth. The historical negative growth is understandable when considering the recent loss of sales to cogeneration and the fact that this 15-year historical period includes the Great Recession, when industrial sales were significantly depressed.

Table 2

		Sales Data				% Growth	
Class	Item	_2005	_2019	_2020	_2034	History	Forecast
Residential	Nbr Customers	505,910	636,386	645,797	762,544	1.7	1.2
	kWh per Customer	14,792	12,843	12,623	12,787	-1.0	0.1
	Total GWh Sales	7,484	8,173	8,152	9,751	0.6	1.3
Commercial	Nbr Customers	83,370	97,544	98,185	114,483	1.1	1.1
	kWh per Customer	84,026	75,137	75,134	64,278	-0.8	-1.1
	Total GWh Sales	7,005	7,329	7,377	7,359	0.3	0.0
Industrial	Total GWh Sales	6,645	5,694	5,812	6,587	-1.1	0.9
All Sales	Total GWh Sales	23,138	22,661	22,952	24,467	-0.1	0.5

[1] The National Bureau of Economic Research sets the dates of the Great Recession as beginning in December 2007 and ending in June 2009.

DESC'S PEAK DEMAND FORECAST

Q. WHAT ARE THE PRINCIPAL RESULTS OF DESC'S PEAK DEMAND FORECAST STUDY?

A. As explained in "The Peak Demand Forecast" study attached as Exhibit No. ___(JML-2), the principal results are that DESC expects its winter peak demand to be higher than its summer peak demand over the 15-year planning horizon under normal weather conditions. Table 3 below shows the forecasted peaks by season using the industry convention that the winter season follows the summer season.

Table 3

	Gross Peak Demands		Demand Response		Net Peak Demands	
	Summer	Winter	Summer	Winter	Summer	Winter
	MW	MW	MW	MW	MW	MW
2020	4,816.0	4,891.0	227.0	224.4	4,589.0	4,666.6
2021	4,847.0	4,923.7	228.0	225.9	4,619.0	4,697.9
2022	4,878.6	4,954.6	229.0	227.7	4,649.6	4,726.9
2023	4,905.2	4,963.5	230.0	230.2	4,675.2	4,733.3
2024	4,916.2	4,992.0	231.0	234.0	4,685.2	4,758.0
2025	4,941.0	5,021.6	232.0	239.4	4,709.0	4,782.2
2026	4,966.7	5,050.5	233.0	248.9	4,733.7	4,801.6
2027	4,992.7	5,076.5	234.0	261.1	4,758.7	4,815.4
2028	5,019.2	5,101.7	235.0	275.4	4,784.2	4,826.3
2029	5,041.1	5,151.7	236.0	276.4	4,805.1	4,875.3
2030	5,090.1	5,208.7	237.0	277.4	4,853.1	4,931.3
2031	5,146.1	5,265.7	238.0	278.4	4,908.1	4,987.3
2032	5,201.1	5,318.7	239.0	279.4	4,962.1	5,039.3
2033	5,256.1	5,374.7	240.0	280.4	5,016.1	5,094.3
2034	5,309.1	5,427.7	241.0	281.4	5,068.1	5,146.3

Note: Winter season follows summer.

The gross peak demand, also referred to as the total internal demand, represents the system peak demand before dispatching any demand response ("DR") resources. The net peak demand, also known as the net internal demand or firm peak demand, represents the peak demand after all DR resources are dispatched. The DR forecast represents the Company's existing DR resources plus new winter DR programs that have not yet been developed.

Q. HOW DOES DESC FORECAST ITS SEASONAL PEAK DEMANDS?

A. The details of the peak demand forecasting process are explained more fully in the study attached as Exhibit No. ___(JML-2). However, the basic methodology uses the customer and energy sales forecast as the driver for growth and uses the load characteristics of each customer class captured in the Company's Load Research Program to develop the resulting peak demand. After this base level of demand is calculated, adjustments are made to the forecast to account for the incremental impacts of energy efficiency ("EE") (both from Company demand side management ("DSM") programs and federal and other mandates) and incremental net energy metering on the system. Table 4 below shows the components and the process to develop the summer peak forecast for 2020.

Table 4

			Energy Forecast		Summer Peak		
Year	Class	DESC	Customer	GWh Sales	kW Per	Factor	Peak Demand
2020	10.0	Res	645,797	.	3.294	1.0099	2,147
	10.2	Res.Adj	.	.	.	.	-10
	20.0	Com	98,185	.	15.757	1.0099	1,562
	30.0	Ind	.	5812.0	0.915	1.0099	613
	30.1	Ind.DR	.	.	.	.	193
	30.2	Ind.Adj	.	.	.	.	15
	60.0	PSL	.	153.8	0.127	1.0099	2
	70.0	OPA	.	519.0	1.481	1.0099	89
	92.0	Muni	.	871.0	1.727	1.0099	173
	98.1	CoUse	.	.	.	.	31
	98.5	DR	.	.	.	.	-226
	98.7	EE	.	.	.	.	0
2020			.	.	.	.	4,589

The 4-hour factor in the table, *i.e.*, 1.0099, applied in the summer season converts the forecast for the 4-hour band of hours, *i.e.*, 2 p.m. to 6 p.m., to a one-hour basis. The winter peak does not need to be converted since it is projected on a one-hour basis. The calculation for the residential and commercial classes is straightforward. For example, in the case of the residential 2020 summer, the peak demand is 2,147 Megawatts ("MW") and the calculation is:

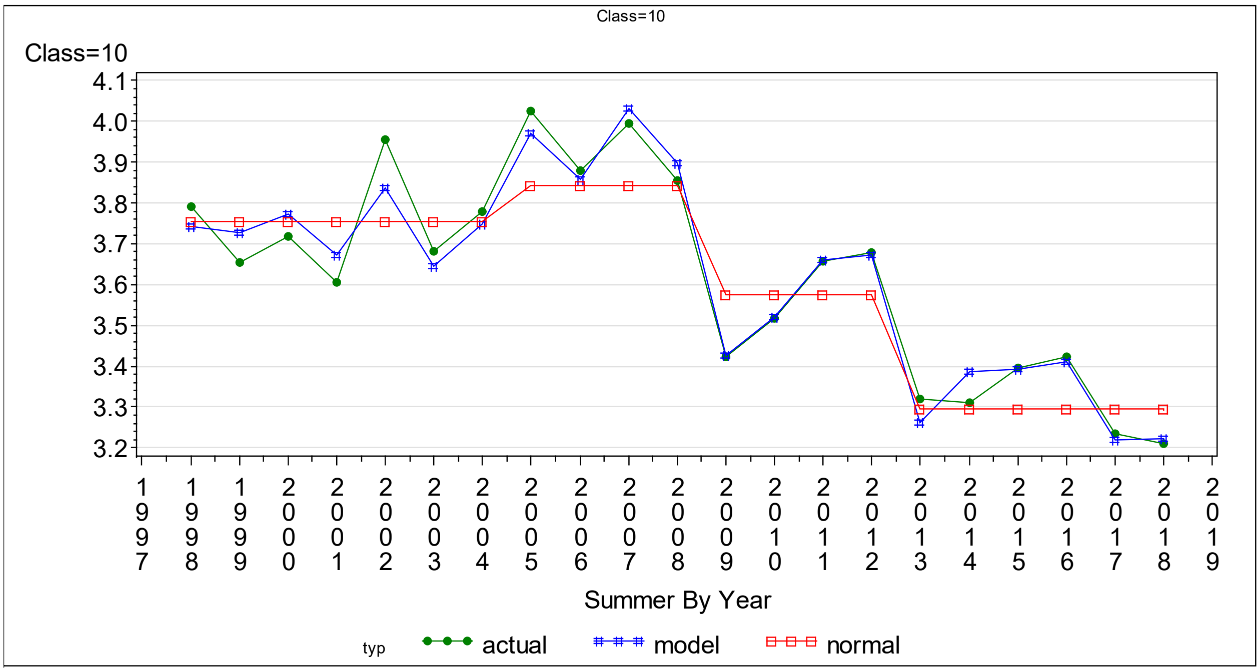
645,797 * 3.294 *1.0099 /1000 = 2,148 MW ≈ 2,147 MW[2].

The kW per customer value of 3.294 is derived from DESC's Load Research Program and is the weather normalized average kW per customer value taken over

[2] South Carolina Act No. 62 of 2019 required the 2020 IRP to incorporate several DSM scenarios which necessitated moving the forecasted data from the SAS platform to the EXCEL platform and back to SAS. This resulted in a round-off error of about 1 MW in some instances.

the last few years. The following chart shows the results of a statistical regression analysis which is its source.

Chart 1



The red straight line in the graph is the weather normalized average kW per customer averaged over several years. In this case, the most recent average is 3.294.

For the industrial class, the number of hours in the year comes into play. For example, in the case of the industrial 2020 summer, the calculation is:

(5,812/ (8,760/1,000)) * 0.915 * 1.0099 = 613 MW.

It may be worth noting that the kW per kilowatt hour ("kWh") load characteristic can be referred to as the demand ratio and is equal to the reciprocal of the load factor.

The following table shows the development of the 2020 winter peak, that is, the peak occurring in the 2020/2021 winter season.

Table 5

				Energy Forecast		Winter Peak	
wyear	year	Class	DESC	Customer	GWh Sales	kW Per	Peak Demand
2020	2021	10.0	Res	655,077	.	3.916	2,564
		10.2	Res.Adj	.	.	.	-14
		20.0	Com	98,711	.	13.756	1,358
		30.0	Ind	.	5890.0	0.768	516
		30.1	Ind.DR	.	.	.	188
		60.0	PSL	.	153.8	0.155	3
		70.0	OPA	.	518.0	1.220	72
		92.0	Muni	.	871.0	1.726	172
		98.1	CoUse	.	.	.	31
		98.5	DR	.	.	.	-223
		98.7	EE	.	.	.	0
2020	2021			.	.	.	4,667

The winter peak demands are calculated in the same way as the summer except there is no need for the 1.0099 factor which increased the summer four-hour average peak forecast by about 1% to represent a one-hour peak demand.

Q. WHAT ARE THE CATEGORIES IN THE TABLES THAT ARE ENTRIES INSTEAD OF CALCULATIONS?

A. The rows listed with classes of customer equal to 10.0, 20.0, 30.0, 60.0, 70.0 and 92.0 represent calculations of the base peak demand forecast for the residential, commercial, industrial, public street lighting, other public authorities and municipal classes of customers respectively. The other rows represent adjustments to this base forecast. The following table explains what they represent.

Table 6

Category	Description
10.2 Res.Adj.	Residential adjustments related to federal mandates of appliance and lighting efficiencies.
30.1 Ind.DR	Interruptible load in the industrial class
98.1 CoUse	Effect of Company's Use of power
98.5 DR	Demand response to include interruptible loads and standby generation
98.7 EE	Impacts related to the Company's EE programs.

Q. WHY DOES DESC PROJECT ITS WINTER PEAK TO BE HIGHER THAN ITS SUMMER PEAK?

A. The prominence of the winter peak demand relative to the summer peak demand is a consequence of changes in customer usage patterns resulting from energy efficiency and conservation having different seasonal impacts. For example, based on the Company's load research studies, the kW per customer impact on the summer peak demand has decreased from about 3.843 kW prior to the Great Recession to about 3.294 kW today, while the winter peak demand decreased from about 4.105 kW to about 3.916 kW. This reflects an approximate 14% decrease in summer peak demand and only about a 5% decrease in winter peak demand. For the average commercial customer, the decrease is about 11% in summer from 17.724 kW per customer to 15.757 kW and only about 3% in winter from 14.282 kW to 13.756 kW per customer. This data clearly demonstrates there are more effective opportunities to conserve electricity in summer than winter.

DESC'S FORECAST SCENARIOS

Q. WHY ARE FORECAST SCENARIOS INCLUDED IN THE 2020 IRP?

A. One of the requirements legislated in the South Carolina Act No. 62 of 2019 ("Act No. 62") for IRPs was to include "a long-term forecast of the utility's sales and peak demand under various reasonable scenarios." In response, DESC included several scenarios that presented risks to the baseline forecast of sales and peak demands.

Q. WHAT FORECAST SCENARIOS WERE CONSIDERED?

A. There were three categories of scenarios presented: a high and low economic scenario, a wholesale scenario and an electric vehicle ("EV") scenario.

Q. EXPLAIN THE HIGH AND LOW ECONOMIC SCENARIO TO THE FORECAST.

A. The economic scenario considered alternative growth rates to the base forecast, *i.e.,* a high and low forecast. By analyzing growth over past 15-year segments and making appropriate adjustments, DESC determined that reasonable bounds on the risk of change in the load growth forecast are a high of 1.7% and a low of 0.25%, per year as compared to the 0.5% growth projection for energy in the accepted forecast. The following table shows the impact on sales and peak demands should the system grow at these alternate rates.

Table 7

High Scenario: Change from Base			
	Annual	Peak Demands	
	Sales	Summer	Winter
	GWH	MW	MW
2020	0.0	0.0	0.0
2021	297.9	59.9	60.9
2022	598.0	121.4	123.3
2023	905.1	184.2	186.4
2024	1,214.1	247.7	251.6
2025	1,531.5	313.2	318.3
2026	1,856.1	380.1	386.5
2027	2,186.3	448.6	456.1
2028	2,521.5	518.6	527.1
2029	2,864.6	589.7	602.6
2030	3,227.9	665.7	681.2
2031	3,602.1	745.0	762.3
2032	3,993.9	826.6	845.3
2033	4,394.6	910.6	931.2
2034	4,804.4	996.9	1,019.1

Low Scenario: Change from Base			
	Annual	Peak Demands	
	Sales	Summer	Winter
	GWH	MW	MW
2020	0.0	0.0	0.0
2021	-49.8	-10.0	-10.2
2022	-99.2	-20.1	-20.5
2023	-149.1	-30.4	-30.7
2024	-198.6	-40.5	-41.1
2025	-248.7	-50.9	-51.7
2026	-299.2	-61.3	-62.3
2027	-349.9	-71.8	-73.0
2028	-400.7	-82.4	-83.8
2029	-451.9	-93.0	-95.1
2030	-505.5	-104.2	-106.7
2031	-560.0	-115.8	-118.5
2032	-616.3	-127.6	-130.4
2033	-673.2	-139.5	-142.7
2034	-730.6	-151.6	-155.0

Q. EXPLAIN THE WHOLESALE FORECAST SCENARIO.

A. DESC has two wholesale customers that are municipalities. While long time customers and partners, these customers are essentially tied to DESC by a service contract. When the contracts expire, these customers will canvass the power markets for energy providers including DESC. DESC will only retain their business if it can provide reliable service at a competitive price. The following table shows the sales and peak demands included in the DESC forecast related to this wholesale business.

Table 8

Wholesale Portion of Base Forecast			
	Annual	Peak Demands	
	Sales	Summer	Winter
	GWH	MW	MW
2020	871.0	148	147
2021	871.0	148	147
2022	873.0	149	147
2023	876.3	149	148
2024	879.6	150	148
2025	882.9	151	149
2026	886.3	151	150
2027	889.8	152	150
2028	893.3	153	151
2029	896.8	154	152
2030	900.3	154	152
2031	903.9	155	153
2032	908.0	156	154
2033	912.1	157	155
2034	916.2	157	156

One of these contracts expires on December 31, 2022, but a Company has an option to extend it one more year. The other contract expires on May 31, 2026. DESC has had a long, mutually satisfactory history of service with these customers, which suggests a positive outlook for continuing the relationship. Regardless, there is still a few years to resolve this uncertainty in its resource planning.

Q. EXPLAIN THE ELECTRIC VEHICLE SCENARIO TO THE FORECAST.

A. Each year there are more electric vehicles on the road and more infra-structure to support them. It is generally believed that the future of automotive transportation is electric. The only questions are when and how fast the transition from fossil fuels occurs. An electric car is expected to have an operating efficiency of 4 miles per kWh. At a cost of $0.14 per kWh, an EV should get about 28.6 miles per dollar. A gasoline powered car getting 30 miles per gallon with a $2.40 cost per gallon has an operating efficiency of 12.5 miles per dollar. Additionally, it has been estimated that the drivetrain of a gasoline powered car has over 2,000 moving parts while an electric vehicle drivetrain has fewer than 20. Clearly an EV has an operating and maintenance advantage over a traditional car. If cars drive about 15,000 miles per year, a single EV could add about 3,750 kWh per year to DESC's system. A large number of EVs coming onto the system can have a significant impact, which is why a scenario analysis of potential EV loads is useful. The following table shows the impact on sales associated with three levels of EV saturation. The core assumption is that there are about 645,797 households on the DESC system with an average of 2.1 cars per household.

Table 9

		EV Scenarios		
	DESC	2034 Saturation Scenario		
	Vehicles	1%	5%	10%
2020	1,356,174	1,085	1,085	1,085
2021	1,375,662	1,293	2,256	2,806
2022	1,393,867	1,505	3,457	4,572
2023	1,411,311	1,722	4,686	6,379
2024	1,428,727	1,943	5,944	8,229
2025	1,446,356	2,170	7,232	10,124
2026	1,464,460	4,100	13,180	22,846
2027	1,482,268	6,077	19,269	35,871
2028	1,499,629	8,098	25,494	49,188
2029	1,516,523	10,161	31,847	62,784
2030	1,532,794	12,262	38,320	76,640
2031	1,550,199	13,177	48,444	96,887
2032	1,567,528	14,108	58,782	117,565
2033	1,584,626	15,054	69,327	138,655
2034	1,601,342	16,013	80,067	160,134

Under the 5% scenario, DESC would expect 80,067 EVs on its system and, with a load of 3,750 kWh per car, the total system load would be about 300 GWh, which is only a 1.2% increase in the projected 2034 sales. However, if the saturation turns out to be 80% instead of 5%, then the impact is 4,804 GWh or about 20% of projected 2034 sales. DESC will continue to monitor developments in this market.

DESC'S RESERVE MARGIN POLICY

Q. WHAT IS DESC'S CURRENT RESERVE MARGIN POLICY USED IN DEVELOPING ITS RESOURCE PLAN?

A. Table 10 below summarizes DESC's reserve margin policy.

Table 10
Minimum Reserve Margin as Percent of Seasonal Peak Demand

	SUMMER	WINTER
Base Level	12%	14%
Peaking Level	14%	21%
Increment for Peaking	2%	7%

The Commission accepted these reserve margins in Order No. 2018-322(A).

Q. HOW DID DESC DETERMINE ITS RESERVE MARGIN POLICY?

A. The study titled "2018 Reserve Margin Study (Updated)" is attached as Exhibit No. __ (JML-3). The study explains the three components that make up the reserve margin, *i.e.*, the operating reserves required under the Virginia-Carolina

("VACAR") Reserve Sharing Agreement, the reserves to cover the demand-side risk, and the reserves to cover the supply-side risk. Under the VACAR Reserve Sharing Agreement, DESC is always required to have about 200 MW in reserves with half of that amount synchronized to the grid and the other half available within 10-minutes. The VACAR requirement is recalculated annually. It may change from year to year by one or two MW but is always around 200 MW. The reserves required to cover the demand-side risk are developed through a statistical study of the system's load response to changing weather. The reserves required to address the supply side risk are developed by an analysis of the Company's experience with generating unit outages.

Q. CAN YOU DESCRIBE THE DEMAND SIDE RISK ANALYSIS?

A. The demand side risk analysis used statistical regression techniques to quantify the weather sensitivity of peak loads in the winter and summer seasons separately. The regression procedure used a stepwise algorithm that considers all the explanatory variables available and choses the best set of variables to include in the regression model based on goodness of fit to the data. In both the summer and winter seasons, the stepwise algorithm chose a quadratic formulation *i.e.,* a second-degree equation, when all days with degree days above zero were used in the estimation process. When the days were restricted to the 100 hottest in summer and coldest in winter, the stepwise algorithm chose a quadratic formulation for winter and a linear formulation for summer. As a final step using the 100-day scenario, the stepwise procedure was forced to estimate a linear model in summer and a quadratic model in winter. Thus, three separate equations for each season were developed: a quadratic equation using all the heating or cooling days in the season; a quadratic formula using a restricted number of days; and, finally, a linear equation using a restricted number of days.

Q. WHAT WERE THE ESTIMATES OF DEMAND-SIDE RISK FROM THE DIFFERENT FORMULATIONS OF STATISTICAL ESTIMATION?

A. Table 11 below shows the estimated demand risk by season based on all three equations.

Table 11

Demand Risk Related to Extreme Weather (MW)		
	Summer	**Winter**
Quadratic, All Days	**245**	**557**
Quadratic, Restricted Days	**281**	**615**
Linear, Restricted Days	**263**	**507**

Even though the results using the quadratic regression model on all heating or cooling days were used to develop DESC's reserve margin, the other formulations clearly do not provide a significantly different estimate.

Q. THE WINTER DEMAND SIDE RISK IS MUCH HIGHER THAN SUMMER. CAN YOU CORROBORATE THAT LEVEL OF RISK IN WINTER?

A. Yes. DESC's demand forecasting methodology and class load characteristics can be used to corroborate this level of risk in the winter. As previously discussed, DESC expects residential customers to contribute about 3.916

kW per customer at the time of winter peak demand and commercial customers to contribute about 13.756 kW. In 2003, DESC experienced a very cold winter and our load research program estimated the residential contribution to peak then to be 4.649 kW per customer and the commercial contribution, 15.391 kW. Table 12 below shows the potential demand risk if next winter is very cold and residential and commercial customers respond in a similar manner as they did in 2003.

Table 12

2020 Demand-side Winter Weather Risk				
	Customers	2003 kW per Customer	Normal kW per Customer	Risk Estimate
Residential	655,077	4.649	3.916	480 MW
Commercial	98,711	15.391	13.756	161 MW
Total Demand Risk				**641 MW**

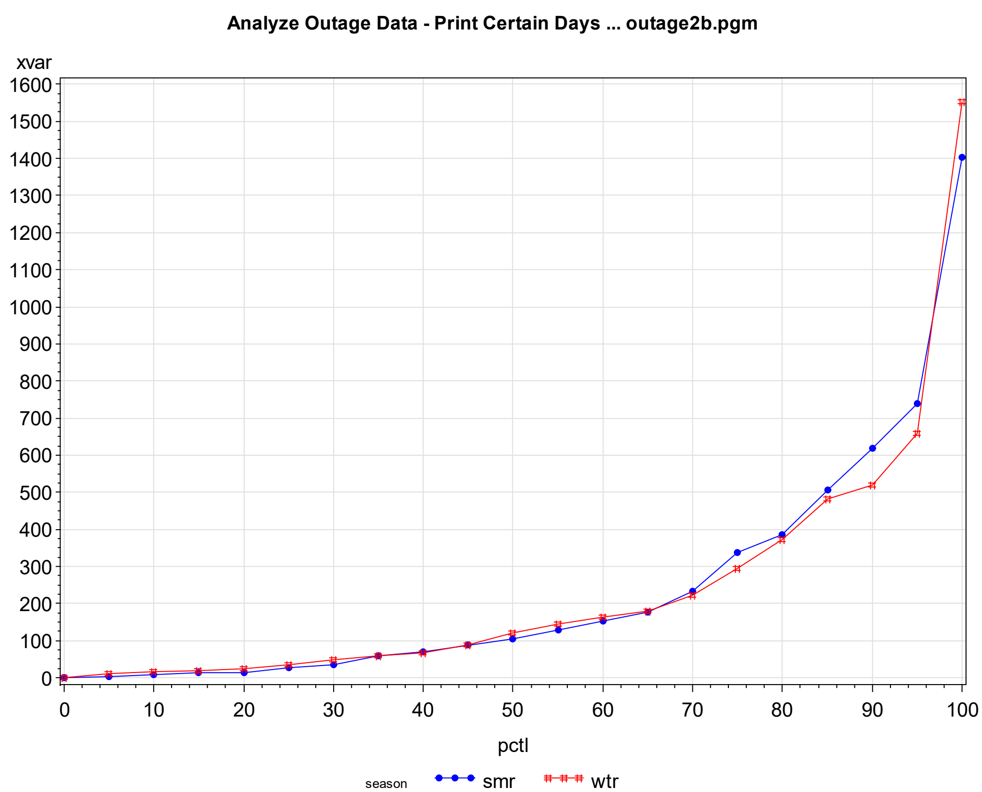
The demand-side winter weather risk estimate developed here using load research data of 641 MW is reasonably close to the statistical estimate of 557 MW used in the reserve margin analysis.

Q. CAN YOU DESCRIBE THE SUPPLY SIDE RISK ANALYSIS?

A. To quantify the supply-side risk, the forced outage history of DESC's generating units was analyzed. By calculating the number of MWs of generation that was forced out or de-rated on each day of the summer and winter, a distribution of outage was developed for the summer season and for the winter season. For summer, the daily outages during the months of June, July and August were studied for the years 2010-2017. For winter, the months of December, January and

February were used. The resulting number of days used for summer and for winter was greater than 700 each season. The following is the distribution in graphical form showing the accumulated MW out by the percentile in the probability distribution. The 70th percentile was chosen for the reserve margin policy.

Chart 2



Q. WHAT WERE THE OVERALL RESULTS?

A. Table 13 below shows the three components that make up the reserve margin, *i.e.*, the VACAR operating reserves, the reserves for the demand-side risk and the reserves for the supply-side risk.

Table 13

Reserve Margin for Summer and Winter Peak Periods		
	Summer	**Winter**
VACAR Operating	**200**	**200**
Demand-Side Risk	**245**	**556**
Supply-Side Risk	**234**	**223**
Total Reserve MW	**679**	**979**
Normal Peak Demand	**4763**	**4852**
Reserve Margin %	**14.3%**	**20.2%**
Reserve Margin Policy	**14%**	**21%**

The results of the study support the continued use of a 14% minimum reserve margin in summer and 21% in winter.

Q. USING THE DEMAND SIDE RISK AND THE SUPPLY SIDE RISK DISCUSSED ABOVE, CAN YOU CALCULATE THE PROBABILITY OF THE LOAD EXCEEDING THE AVAILABLE CAPACITY?

A. Yes, I can. The probability distribution of demand side risk is summarized in Table 2 of Exhibit No. ___(JML-3) and the probability distribution of supply side risk in Table 3. Using the Convolution Formula from statistical theory, the joint probability distribution can be calculated which will combine both sources of risk. Assuming a 21% reserve margin in the winter, the probability that DESC does not have 200 MW in reserves to meet its VACAR obligation is 7.7%. The probability that DESC does not have enough capacity to serve its firm load is 3.7%. This means that over the course of ten years the probability of a capacity shortfall in at least one of the ten years is 55% and of not serving the load, 31%.

Q. IS THE 21% WINTER RESERVE MARGIN UNREASONABLE?

A. No, based on the analysis of demand side and supply side, the 21% reserve margin is reasonable. It may be useful to note that the PJM Regional Transmission Organization ("RTO") has a winter reserve target of 28%.[3]

Q. IS 28% PJM'S RESERVE MARGIN?

A. No. PJM's Installed Reserve Margin ("IRM") is 15.5% based on their summer peak demand. The 28% winter reserve target is based on the peak in January with 22% and 24% for December and February respectively. The summer reserve margin is the binding constraint for resource planning

Q. HOW CAN 15.5% BE THE BINDING CONSTRAINT AGAINST A 28% CONSTRAINT?

A. The PJM RTO is a summer peaking system. Under normal weather conditions PJM expects their summer peak to be about 15% higher than their winter peak. Thus, the resources needed to have a 15.5% reserve margin in summer would produce a 32.8% winter reserve margin on the winter peak which satisfies the winter constraint.

Q. DOES THIS CONCLUDE YOUR DIRECT TESTIMONY?

A. Yes.

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[3] See PJM's "2019 PJM Reserve Requirement Study" published on October 17, 2019. The weblink is: https://www.pjm.com/-/media/planning/res-adeq/2019-pjm-reserve-requirement-study.ashx?la=en

ENERGY FORECAST DOCUMENTATION

SHORT RANGE AND LONG RANGE

FOR 2020 BUDGET AND BEYOND

Short Range Methodology

This section presents the development of the short-range electric sales forecasts for the Company. Two years of monthly forecasts for electric customers, average usage, and total usage were developed according to Company class and rate structures, with industrial customers further categorized individually or into SIC (Standard Industrial Classification) codes. Residential customers were classified by housing type (single family, multi-family, and mobile homes), rate, and by a statistical estimate of weather sensitivity. For each forecasting group, the number of customers and either total usage or average usage was estimated for each month of the forecast period.

The short-range methodologies used to develop these models were determined primarily by available data, both historical and forecast. Monthly sales data by class and rate are generally available historically. Daily heating and cooling degree data for Columbia and Charleston are also available historically and were projected using a 15-out-of-17-year average of the daily values, after dropping the high and low values for each day. Industrial production indices are also available by SIC on a quarterly basis and can be transformed to a monthly series. Therefore, sales, weather, industrial production indices, and time dependent variables were used in the short-range forecast. In general, the forecast groups fall into two classifications, weather sensitive and non-weather sensitive. For the weather sensitive classes, regression analysis was the methodology used, while for the non-weather sensitive classes regression analysis or time series models based on the autoregressive integrated moving average (ARIMA) approach of Box-Jenkins were used.

The short-range forecast developed from these methodologies was also adjusted for federally mandated lighting programs, net energy metering solar, new industrial loads, terminated contracts, or economic factors as discussed in Section 3.

Regression Models

Regression analysis is a method of developing an equation which relates one variable, such as usage, to one or more other variables which help explain fluctuations and trends in the first. This method is mathematically constructed so that the resulting combination of explanatory variables produces the smallest squared error between the historic actual values and those estimated by the regression equation. The output of the regression analysis provides an equation for the variable being explained. Several statistics which indicate the success of the regression analysis fit are shown for each model. Several of these indicators are R^2, Root Mean Squared Error, Durbin-Watson Statistic, F-Statistic, and the T-Statistics of the Coefficient. PROC REG of SAS was used to estimate all regression models. PROC AUTOREG of SAS was used if significant autocorrelation, as indicated by the Durbin-Watson statistic, was present in the model.

Two variables were used extensively in developing weather sensitive average use models: heating degree days ("HDD") and cooling degree days ("CDD"). The values for HDD and CDD are the average of the values for Charleston and Columbia. The base for HDD was 60º and for CDD was 75º. In order to account for cycle billing, the degree day values for each day were weighted by the number of billing cycles which included that day for the current month's billing. The daily weighted degree day values were summed to obtain monthly degree day values. Billing sales for a calendar month may reflect consumption that occurred in the previous month based on weather conditions in that period and consumption occurring in the current month. Therefore, this method more accurately reflects the impact of weather variations on the consumption data.

The development of average use models began with plots of the HDD and CDD data versus average use by month. This process led to the grouping of months with similar average use patterns. Summer and winter groups were chosen, with the summer models including the months of May through October, and the winter models including the months of November through April. For each of the groups, an average use model was developed. Total usage models were developed with a similar methodology for the municipal customers. For these customers, HDD and CDD were weighted based on monthly calendar weather. Simple plots of average use over time revealed significant changes in average use for some customer groups. Three types of variables were used to measure the effect of time on average use:

1. Number of months since a base period;
2. Dummy variable indicating before or after a specific point in time; and,
3. Dummy variable for a specific month or months.

Some models revealed a decreasing trend in average use, which is consistent with conservation efforts and improvements in energy efficiency. However, other models showed an increasing average use over time. This could be the result of larger houses, increasing appliance saturations, lower real electricity prices, and/or higher real incomes.

ARIMA Models

Autoregressive integrated moving average ("ARIMA") procedures were also used in developing the short-range forecasts. For various class/rate groups, they were used to develop customer estimates, average use estimates, or total use estimates.

ARIMA procedures were developed for the analysis of time series data, i.e., sets of observations generated sequentially in time. This Box-Jenkins approach assumes that the behavior of a time series is due to one or more identifiable influences in its history. This method recognizes three effects that a particular observation may have on subsequent values in the series:

1. A decaying effect leads to the inclusion of autoregressive (AR) terms;
2. A long-term or permanent effect leads to integrated (I) terms; and,
3. A temporary or limited effect leads to moving average (MA) terms.

Seasonal effects may also be explained by adding additional terms of each type (AR, I, or MA).

The ARIMA procedure models the behavior of a variable that forms an equally spaced time series with no missing values. The mathematical model is written:

$$Z_t = u + Y_i\,(B)\,X_{i,t} + q\,(B)\,/\,f\,(B)\,a_t$$

This model expresses the data as a combination of past values of the random shocks and past values of the other series, where:

t	indexes time
B	is the backshift operator, that is $B\,(X_t) = X_{t-1}$
Z_t	is the original data or a difference of the original data
$f(B)$	is the autoregressive operator, $f(B) = 1 – f_1\,B - \ldots - f_1\,B^p$
u	is the constant term
$q(B)$	is the moving average operator, $q\,(B) = 1 - q_1\,B - \ldots - q_q\,B^q$
a_t	is the independent disturbance, also called the random error
$X_{i,t}$	is the ith input time series
$Y_i(B)$	is the transfer function weights for the ith input series (modeled as a ratio of polynomials)
$Y_i(B)$	is equal to $w_i\,(B)/\,d_i\,(B)$, where $w_i\,(B)$ and $d_i\,(B)$ are polynomials in B.

The Box-Jenkins approach is most noted for its three-step iterative process of identification, estimation, and diagnostic checking to determine the order of a time series. The autocorrelation and partial autocorrelation functions are used to identify a tentative model for univariate time series. This tentative model is estimated. After the tentative model has been fitted to the data, various checks are performed to see if the model is appropriate. These checks involve analysis of the residual series created by the estimation process and often lead to refinements in the tentative model. The iterative process is repeated until a satisfactory model is found.

Many computer packages perform this iterative analysis. PROC ARIMA of (SAS/ETS)[2] was used in developing the ARIMA models contained herein. The attractiveness of ARIMA models comes from data requirements. ARIMA models utilize data about past energy use or customers to forecast future energy use or customers. History on energy use and customers serves as a proxy for all the measures of factors underlying energy use and customers when other variables were not available. Univariate ARIMA models were used to forecast average use or total usage when weather-related variables did not significantly affect energy use or alternative independent explanatory variables were not available.

Electric Sales Assumptions

For short-term forecasting, over 30 forecasting groups were defined using the Company's customer class and rate structures. Industrial (Class 30) Rate 23 was further divided using SIC codes. In addition, more than thirty large industrial customers were individually projected. The residential class was disaggregated into several sub-groups, starting first with rate. Next, a regression analysis was done to separate customers into two categories, “more weather-sensitive” and “less weather sensitive”. The former group is associated with higher average use per customer in winter months relative to the latter group. Finally, these categories were divided by housing type (single family, multi-family, and mobile homes). Each municipal account represents a forecasting group and was also individually forecast. Discussions were held with Industrial Marketing and Economic Development representatives within the Company regarding prospects for industrial expansions or new customers, and adjustments made to customer, rate, or account projections where appropriate. Table 1 contains the definition for each group and Table 2 identifies the methodology used and the values forecasted by forecasting groups.

The forecast for Company Use is based on historic trends and adjusted for Summer 1 nuclear plant outages. Unaccounted energy, which is the difference between generation and sales and represents for the most part system line losses, is usually between 4-5% of total territorial sales. The average annual line loss for the three previous years was 4.7%, and this value was assumed throughout the forecast. The monthly allocations for unaccounted use were based on a regression model using normal total degree-days for the calendar month and total degree-days weighted by cycle billing. Adding Company Use and unaccounted energy to monthly territorial sales produces electric generation requirements.

TABLE 1 Short-Term Forecasting Groups

Number	Class Name	Designation	Comment
10	Residential Less Weather-Sensitive	Single Family	Rates 1, 2, 5, 6, 8, 18, 25, 26, 62, 64 67, 68, 69
		Multi Family	
910	Residential More Weather-Sensitive	Mobile Homes	
20	Commercial Less Weather-Sensitive	Rate 9	Small General Service
		Rate 12	Churches
		Rate 20, 21	Medium General Service
		Rate 22	Schools
		Rate 24	Large General Service
		Other Rates	3, 10, 11, 14, 16, 18, 25, 26 29, 62, 67, 69
920	Commercial Space Heating More Weather-Sensitive	Rate 9	Small General Service
30	Industrial Non-Space Heating	Rate 9	Small General Service
		Rate 20, 21	Medium General Service
		Rate 23, SIC 22	Textile Mill Products
		Rate 23, SIC 24	Lumber, Wood Products, Furniture and Fixtures (SIC Codes 24 and 25)
		Rate 23, SIC 26	Paper and Allied Products
		Rate 23, SIC 28	Chemical and Allied Products
		Rate 23, SIC 30	Rubber and Miscellaneous Products
		Rate 23, SIC 32	Stone, Clay, Glass, and Concrete
		Rate 23, SIC 33	Primary Metal Industries; Fabricated Metal Products; Machinery; Electric and Electronic Machinery, Equipment and Supplies; and Transportation Equipment (SIC Codes 33-37)
		Rate 23, SIC 99	Other or Unknown SIC Code*
		Rate 27, 60	Large General Service
		Other	Rates 18, 25, and 26
60	Street Lighting	Rates 3, 9, 13, 17, 18, 25, 26, 29, and 69	
70	Other Public Authority	Rates 3, 9, 20, 21, 25, 26, 29, 65 and 66	
92	Municipal	Rate 60, 61	Two Individual Accounts

*Includes small industrial customers from all SIC classifications that were not previously forecasted individually. Industrial Rate 23 also includes Rate 24. Commercial Rate 24 also includes Rate 23.

TABLE 2 Summary of Methodologies Used to Produce the Short-Range Forecast

Value Forecasted	Methodology	Forecasting Groups
Average Use	Regression	Class 10, All Groups Class 910, All Groups Class 20, Rates 9, 12, 20, 22, 24, 99 Class 920, Rate 9 Class 70, Rate 3
Total Usage	ARIMA/ Regression	Class 30, Rates 9, 20, 99, and 23, for SIC = 91 and 99 Class 930, Rate 9 Class 60 Class 70, Rates 65, 66
	Regression	Class 92, All Accounts Class 97, One Account
Customers	ARIMA	Class 10, All Groups Class 910, All Groups Class 20, All Rates Class 920, Rate 9 Class 30, All Rates Except 60, 99, and 23 for SIC = 22, 24, 26, 28, 30, 32, 33, and 91 Class 930, Rate 9 Class 60 Class 70, Rate

Long Range Sales Forecast

Electric Sales Forecast

This section presents the development of the long-range electric sales forecast for the Company. The long-range electric sales forecast was developed for six classes of service: residential, commercial, industrial, street lighting, other public authorities, and municipals. These classes were disaggregated into appropriate subgroups where data was available and there were notable differences in the data patterns. The residential, commercial, and industrial classes are considered the major classes of service and account for over 93% of total territorial sales. A customer forecast was also developed for each major class of service.

For the residential class, forecasts were produced for those customers categorized into two groups, more and less weather sensitive. They were further disaggregated into housing types of single family, multi-family and mobile homes. Residential street lighting was also evaluated separately. These subgroups were chosen based on available data and differences in the average usage levels and/or data patterns. Commercial sales were estimated for four subgroups within this sector: small, medium, large, and “other”. Small commercial sales were limited to Rate 9 usage; medium was based on Rates 12, 20, 21, and 22; large was Rate 24, and other consisted of the special rates shown in Table 1. Average use and customer equations were developed for each commercial subgroup, with the resulting sales projections combined to create the total commercial sales forecast. The industrial class was disaggregated into two digit SIC code classifications for the large general service customers, while smaller industrial customers were grouped into an "other" category. These subgroups were chosen to account for the differences in the industrial mix in the service territory. Except for the residential group, the forecast for sales was estimated based on total usage in that class of service. The number of residential customers and average usage per customer were estimated separately and total sales were calculated as a product of the two.

Forecast Methodology

The forecast for each class of service was developed utilizing an econometric approach. The structure of the econometric model was based upon the relationship between the variable to be forecasted and the economic environment, weather, conservation, and/or price. Development of the models for long-term forecasting was econometric in approach and used the technique of regression analysis. Regression analysis is a method of developing an equation which relates one variable, such as sales or customers, to one or more other variables that are statistically correlated with the first, such as weather, personal income or population growth. Generally, the goal is to find the combination of explanatory variables producing the smallest error between the historic actual values and those estimated by the regression. The output of the regression analysis provides an equation for the variable being explained. In the equation, the variable being explained equals the sum of the explanatory variables each multiplied by an estimated coefficient. Various statistics, which indicate the success of the regression analysis fit, were used to evaluate each model. The indicators were R^2, mean squared Error of the Regression, Durbin-Watson Statistic and the T-Statistics of the Coefficient. PROC REG and PROC AUTOREG of SAS were used to estimate all regression models. PROC REG was used for preliminary model specification, elimination of insignificant variables, and for the final model specifications. Model development also included residual analysis for incorporating dummy variables and an analysis of how well the models fit the historical data, plus checks for any statistical problems such as autocorrelation or multicollinearity. PROC AUTOREG was used if autocorrelation was present as indicated by the Durbin-Watson statistic. Prior to developing the long-range models, certain design decisions were made:

- The multiplicative or double log model form was chosen. This form allows forecasting based on growth rates, since elasticities with respect to each explanatory variable are given directly by their respective regression coefficients. Elasticity explains the responsiveness of changes in one variable (e.g. sales) to changes in any other variable (e.g. price). Thus, the elasticity coefficient can be applied to the forecasted growth rate of the explanatory variable to obtain a forecasted growth rate for a dependent variable. These projected growth rates were then applied to the last year of the short-range forecast to obtain the forecast level for customers or sales for the long-range forecast. This is a constant elasticity model and it is important to evaluate the reasonableness of the model coefficients.
- One way to incorporate conservation effects on electricity is through real prices or time trend variables. Models selected for the major classes would include these variables, if they were statistically significant.
- The remaining variables to be included in the models for the major classes would come from four categories:

1. Demographic variables - Population, households.
2. Measures of economic well-being or activity: real personal income, real per capita income, employment variables, and industrial production indices.
3. Weather variables - average summer/winter temperature or heating and cooling degree-days.
4. Variables identified through residual analysis or knowledge of political changes, major economics events, etc. (e.g., the gas price spike in 2005 attributable to Hurricane Katrina and recession versus non-recession years).

Standard statistical procedures were used to obtain preliminary specifications for the models. Model parameters were then estimated using historical data and competitive models were evaluated on the basis of:

- Residual analysis and traditional "goodness of fit" measures to determine how well these models fit the historical data and whether there were any statistical problems such as autocorrelation or multicollinearity.
- An examination of the model results for the most recently completed full year.
- An analysis of the reasonableness of the long-term trend generated by the models. The major criteria here was the presence of any obvious problems, such as the forecasts exceeding all rational expectations based on historical trends and current industry expectations.
- An analysis of the reasonableness of the elasticity coefficient for each explanatory variable. Over the years a host of studies have been conducted on various elasticities relating to electricity sales. Therefore, one check was to see if the estimated coefficients from Company models were in-line with other studies. As a result of the evaluative procedure, final models were obtained for each class.
- The drivers for the long-range electric forecast included the following variables.

Service Area Housing Starts
Service Area Real Per Capita Income
Service Area Real Personal Income
State Industrial Production Indices
Real Price of Electricity
Average Summer Temperature
Average Winter Temperature

Heating Degree Days
Cooling Degree Days

The service area data included Richland, Lexington, Berkeley, Dorchester, Charleston, Aiken and Beaufort counties, which account for most total territorial electric sales. Service area historic data and projections were used for all classes except for the industrial class. Industrial productions indices were only available on a statewide basis, so forecasting relationships were developed using that data. Since industry patterns are generally based on regional and national economic patterns, this linking of Company industrial sales to a larger geographic index was reasonable.

Economic Assumptions

In order to generate the electric sales forecast, forecasts must be available for the independent variables. The forecasts for the economic and demographic variables were obtained from IHS Markit , Inc. and the forecasts for the price and weather variables were based on historical data. The trend projection developed by IHS Markit is characterized by slow, steady growth, representing the mean of all possible paths that the economy could follow if subject to no major disruptions, such as substantial oil price shocks, untoward swings in policy, or excessively rapid increases in demand.

Average summer temperature (average of June, July, and August temperature) or CDD, and average winter temperature (average of December (previous year), January and February temperature) or HDD were assumed to be equal to the normal values used in the short-range forecast.

After the trend econometric forecasts were completed, reductions were made to account for higher air-conditioning and water-heater efficiencies, DSM programs, net energy metering solar, and the replacement of incandescent light bulbs with more efficient CFL or LED light bulbs. Industrial sales were increased if new customers are anticipated or if there are expansions among existing customers not contained in the short-term projections.

TABLE 3 Long-Term Forecasting Groups

Number	Class Name	Designation	Comment
10	Residential Less Weather-Sensitive	Single Family Multi Family	Classes 10,13,14
910	Residential More Weather-Sensitive	Mobile Homes	Classes 910,913,914
20	Commercial Small, Medium, Large, Other	Rate 9	Small General Service
		Rate 12,20,21,22	Medium General Service
		Rate 24	Large General Service
		Other Rates	Misc rates combined to 999
30	Industrial Non-Space Heating	SIC 22,24,26,28	Textile Mill Products Lumber, Wood Products, Furniture and Fixtures (SIC Codes 24 and 25) Paper and Allied Products Chemical and Allied Products
		SIC 30,32,33	Rubber and Miscellaneous Products Stone, Clay, Glass, and Concrete Primary Metal Industries; Fabricated Metal Products; Machinery; Electric and Electronic Machinery, Equipment and Supplies; and Transportation Equipment (SIC Codes 33-37)
		SIC 99	Other or Unknown SIC Code
		Rate 27, 60	Large General Service
		Other	Kapstone
60	Street Lighting		
70	Other Public Authority		
92	Municipal		Two accounts

TABLE 4 Summary of Methodologies Used to Produce the Long-Range Forecast

Value Forecasted	Methodology	Forecasting Groups
Average Use	Regression, double log	Class 10, All Groups Class 910, All Groups Class 20, small, medium, large, other
Total Usage	Regression, double log	Class 30, SIC 22,24,26,28,30,32,33,99 Kapstone Class 60 Class 70
	Regression, double log	Class 92
Customers	Regression, double log	Class 10 Class 20, small, medium, large, other

Peak Demand Forecast

A demand forecast is made for the summer peak, the winter peak and then for each of the remaining ten months of the year. The summer peak demand forecast, and the winter peak demand forecast is made for each of the six major classes of customers. Customer load research data is summarized for each of these major customer classes to derive load characteristics that are combined with the energy forecast to produce the projection of future peak demands on the system. Interruptible loads and standby generator capacity are captured and used in the peak forecast to develop a firm level of demand. By utility convention the winter season follows the summer season. The territorial peak demands in the other ten months are projected based on historical ratios by season. The months of May through October are grouped as the summer season and projected based on the average historical ratio to the summer peak demand. The other months of the year are similarly projected with reference to the winter peak demand.

The Peak Demand Forecast For 2020

Introduction

The peak demand forecasted growth is determined by the customer and sales forecast using the load characteristics of the different customer classes developed as part of the Company's Load Research Program. This report presents those load characteristics and the resulting peak demand forecast. The methodology for forecasting customers and sales involves many statistical and econometric models, a discussion of which is beyond the scope of this report. However, several comparisons of forecasted to historical growth in customers and sales are included to demonstrate the reasonableness of the forecast.

Table 1 below shows the forecast of the gross peak demand, also known as the total internal demand, for summer and winter. It also shows the projected net peak demand, also known as the firm demand or net internal demand, which is the level of peak demand requiring supply resources to serve. The difference between these two demand concepts is the level of demand response currently available to the Company, most of which is comprised of interruptible customer load.

Table 1

	Gross Peak Demands		Demand Response		Net Peak Demands	
	Summer	Winter	Summer	Winter	Summer	Winter
	MW	MW	MW	MW	MW	MW
2020	4,816.0	4,891.0	227.0	224.4	4,589.0	4,666.6
2021	4,847.0	4,923.7	228.0	225.9	4,619.0	4,697.9
2022	4,878.6	4,954.6	229.0	227.7	4,649.6	4,726.9
2023	4,905.2	4,963.5	230.0	230.2	4,675.2	4,733.3
2024	4,916.2	4,992.0	231.0	234.0	4,685.2	4,758.0
2025	4,941.0	5,021.6	232.0	239.4	4,709.0	4,782.2
2026	4,966.7	5,050.5	233.0	248.9	4,733.7	4,801.6
2027	4,992.7	5,076.5	234.0	261.1	4,758.7	4,815.4
2028	5,019.2	5,101.7	235.0	275.4	4,784.2	4,826.3
2029	5,041.1	5,151.7	236.0	276.4	4,805.1	4,875.3
2030	5,090.1	5,208.7	237.0	277.4	4,853.1	4,931.3
2031	5,146.1	5,265.7	238.0	278.4	4,908.1	4,987.3
2032	5,201.1	5,318.7	239.0	279.4	4,962.1	5,039.3
2033	5,256.1	5,374.7	240.0	280.4	5,016.1	5,094.3
2034	5,309.1	5,427.7	241.0	281.4	5,068.1	5,146.3

Note: Winter season follows summer.

The projected growth rates of both the gross and net peak demands in both the summer and winter seasons over the period 2020-2034 is about 0.7%. The winter peak demands are higher than summer in both cases. For the gross peak demand, the difference is 75 MW in 2020 and 119 MW in 2034. For the net internal demand, the difference is 78 MW in 2020 and in 2034. It is worth noting that the above demands are not reported on a calendar basis. By utility convention, the winter season is thought to follow the summer season. Thus, the winter demands reflect an additional six months of system growth over summer.

Customer Class Characteristics

Except for the recent past, the Company's summer peak demands have always been larger than the winter seasonal peak demands. By examining the forecast methodology and how the customer load characteristics are used, it will be evident why the winter demands may dominate in the future. The following table, Table 2a, contains the components used to derive the summer peak demand forecasts. The residential and commercial classes, i.e., 10.0 and 20.0, are projected using the number of customers in the forecast while the other classes are projected using GWH sales. The adjustment labeled Res.Adj will be explained later. The entry labeled Ind.Adj or class=30.2 represents expansions planned by certain large customers which have been communicated to our customer representatives.

Table 2a – Components Of 2020 Summer Peak Demand Forecast

			Energy Forecast		Summer Peak		
year	class	desc	Customer	GWH Sales	kW Per	Factor	Peak Demand
2020	10.0	Res	645,797	.	3.294	1.0099	2,147
	10.2	Res.Adj	.	.	.	.	-10
	20.0	Com	98,185	.	15.757	1.0099	1,562
	30.0	Ind	.	5812.0	0.915	1.0099	613
	30.1	Ind.DR	.	.	.	.	193
	30.2	Ind.Adj	.	.	.	.	15
	60.0	PSL	.	153.8	0.127	1.0099	2
	70.0	OPA	.	519.0	1.481	1.0099	89
	92.0	Muni	.	871.0	1.727	1.0099	173
	98.1	CoUse	.	.	.	.	31
	98.5	DR	.	.	.	.	-226
	98.7	EE	.	.	.	.	0
2020			.	.	.	.	4,589

Table 1 shows that the summer net peak demand for 2020 is expected to be 4,589 MW which is shown in Table 2a as the sum of several customer components in the column labeled "Peak Demand." The first number in that column is the residential contribution to this total, labeled as class 10.0, and is equal to 2,147 MW. The formula for calculating this result is:

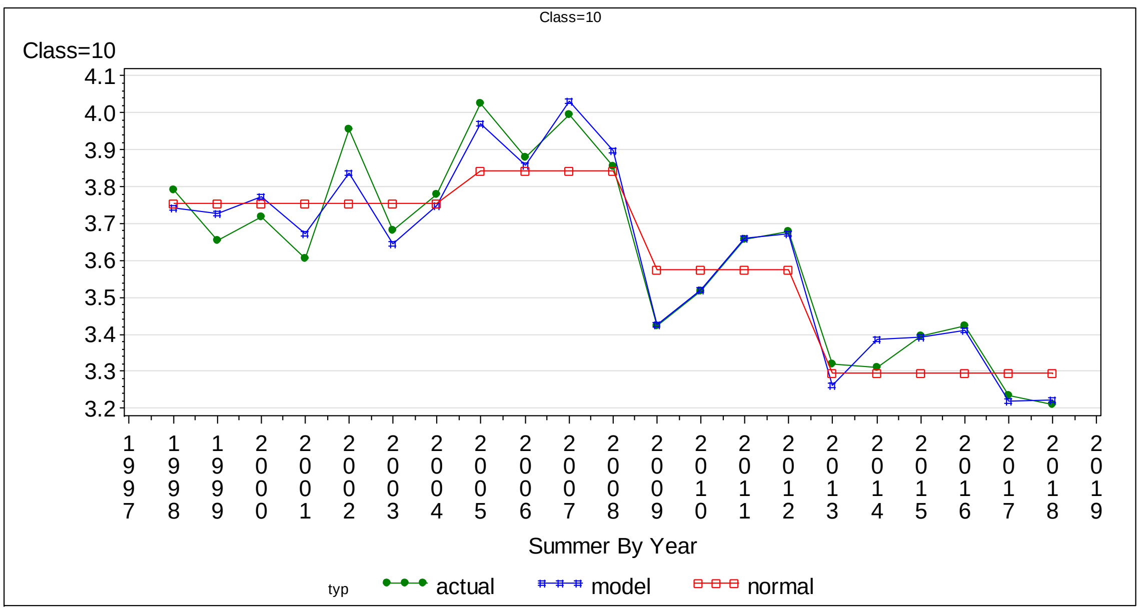
Peak Demand = Number of Customers * kW per customer * factor / 1000
= 645,797 * 3.294 * 1.0099 / 1000

= 2,148 MW ≈ 2,147 MW[1]

The number of residential customers, 645,797, is the average number for 2020 projected in the customer and sales forecast. The load characteristic of 3.294 kW per customer is the projected contribution to the four-hour (2-6 p.m.) summer system peak demand for the average residential customer. The "factor" is the average ratio of the one-hour summer peak demand to the four-hour average. Because the summer peak demand typically occurs in one of these four hours and the residential and commercial loads vary significantly by hour, the Company has used the four-hour period to conduct cost of service allocation studies for many years. The four-hour band is also used to project a more robust summer peak demand which must then be adjusted to the one-hour level, approximately a one percent adjustment.

The following chart shows the derivation of the kW per customer contribution to the summer peak demand for the average residential customer.

Chart 1



The chart shows the actual kW per customer going back to 1998 along with a regression model estimate and then a straight-line average based on normal weather. The regression model allows for this average to decrease over time as shown in the graph. The latest average is about 3.294 kW per customer. The average before the Great Recession[2] of 2008 was about 3.804, a 13% decrease.

[1] South Carolina Act 62 required the 2020 IRP to incorporate several DSM scenarios which necessitated moving the forecasted data from the SAS platform to the EXCEL platform and back to SAS. This resulted in a round-off error of about 1 MW in some instances.

[2] The National Bureau of Economic Research ("NBER") sets the dates of the Great Recession as beginning in December 2007 and ending in June 2009.

The development of the winter peak demand forecast for 2020 is similar. As shown in Table 1, the winter net peak demand forecast for 2020 is 4,667 MW. In the following table, Table 2b, the peak demand of 4,667 MW is shown as the sum of several components.

Table 2b – Components of 2020/2021 Winter Peak Demand Forecast

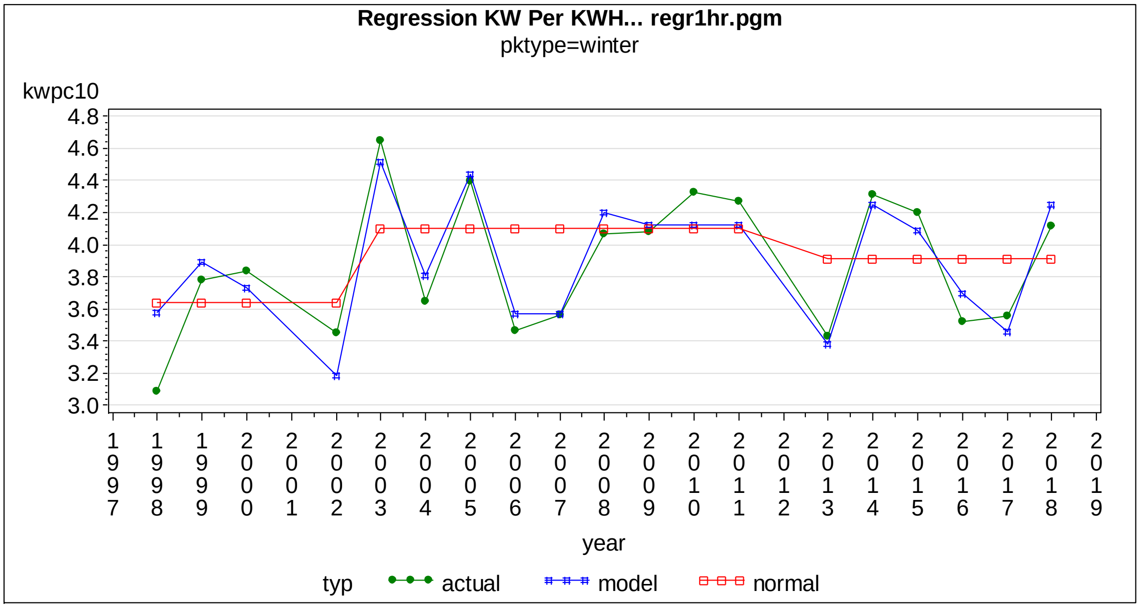
				Energy Forecast		Winter Peak	
wyear	year	class	desc	Customer	GWH Sales	kW Per	Peak Demand
2020	2021	10.0	Res	655,077	.	3.916	2,564
		10.2	Res.Adj	.	.	.	-14
		20.0	Com	98,711	.	13.756	1,358
		30.0	Ind	.	5890.0	0.768	516
		30.1	Ind.DR	.	.	.	188
		60.0	PSL	.	153.8	0.155	3
		70.0	OPA	.	518.0	1.220	72
		92.0	Muni	.	871.0	1.726	172
		98.1	CoUse	.	.	.	31
		98.5	DR	.	.	.	-223
		98.7	EE	.	.	.	0
2020	2021			.	.	.	4,667

The component, labeled class 10.0, is the residential component showing a peak contribution in the winter of 2,564 MW. The formula for calculating this result is:

Peak Demand = Number of Customers * kW per customer / 1000
= 655,077 * 3.916 / 1000
= 2,565 MW ≈ 2,564 MW

The following chart shows the derivation of the kw per customer contribution to the winter peak demand for the average residential customer.

Chart 2



The current estimate of kW per customer of 3.916 reflects a small decrease from a previous period which reaches back to the pre-great recession years. The decrease from 4.132 kW per customer represents only a 5.2% decrease. It is worth noting that the largest kW per customer estimated in the Load Research Program was 4.649 kW per customer occurring in 2003. If circumstances, such as weather, resulted in the 655,077 residential customers increasing their demand from 3.916 to this maximum value of 4.649, it would mean an increase of about 480 MW to their peak contribution, i.e. 655,077*(4.649-3.916).

The development of the commercial demand forecasts is identical to residential since it too relies on the number of customers. In winter then, the normal weather estimate of kW per customer contribution to peak is 13.756 and with a customer forecast for 2020 of 98,711 customers, the estimate of commercial class peak contribution in 2020 is 1,358 MW (=98,711*13.756/1000). Remember the 2020 winter season follows the 2019 summer season. The actual kW per customer contribution to the winter peak in 2003 was 15.391. So, if weather like 2003 occurs during the 2020/2021 winter season, the commercial contribution to peak could increase by 161 MW (=98,711*(15.391-13.756)/1000). Combining the commercial and residential demand related weather risk yields a combined weather risk of 641 MW. The following Table 3 summarizes the results.

Table 3

2019 Combined Residential and Commercial Demand-side Winter Weather Risk				
	Customers	2003 kW per Customer	Normal kW per Customer	Risk Estimate
Residential	655,077	4.649	3.916	480 MW
Commercial	98,711	15.391	13.756	161 MW

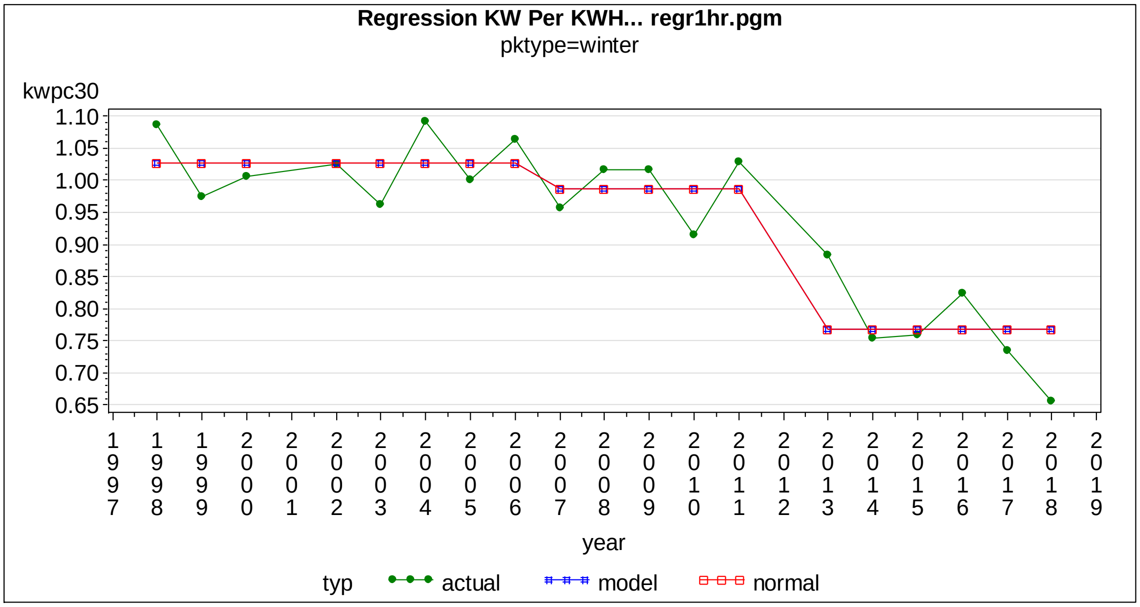
The industrial demand forecast relies on GWH sales, so it may be useful to review its formula. As already noted, the winter net peak demand for 2020 shown in Table 1 is 4,667 MW and this corresponds to the same number in Table 2b shown for 2020 as the sum of several components. The industrial contribution to this total, 516 MW, appears in the middle of the list of components and is labeled as class = “30.0 Ind.” The formula for calculating the industrial demand forecast is:

Peak Demand = (GWH Sales / number of hours) * kW per Average kWh
= (5,890 / 8.760) * 0.768
= 516 MW

The 516 MW represents the firm part of industrial load. The non-firm portion or interruptible part is 188 MW and is shown in Table 2 with the label “Ind.DR” or class=30.1. The interruptible load is estimated using load research interval data for those customers participating in the Company’s interruptible program. The total industrial gross winter peak demand, firm plus interruptible, is 704 MW.

The following chart shows the derivation of the kw per average kWh contribution to the winter peak demand for the average industrial customer.

Chart 3



Since the industrial load does not vary with weather, the model and normal estimates are the same in the chart.

Calculations like those above were made for each class of customer, each season and each year to produce the forecast. The appendix contains charts for each customer class and season as well as a table like Table 2 for the years 2020, 2025, and 2030.

Detail Components of Peak Demand Forecast

The following table, Table 4, shows all the components that comprise the summer peak demand forecast. The rows labeled 10.5, 10.6, 10.7, 10.8 and 10.9 comprise the amount of load grouped under the label “Res.Adj” earlier in Table 2.

Table 4 - SUMMER PEAK DEMAND FORECAST

xclass	desc	_2020	_2021	_2022	_2023	_2024	_2025	_2026	_2027
10.0	Residential	2,147	2,178	2,207	2,235	2,262	2,290	2,319	2,347
10.5	Res SEER	-10	-12	-13	-15	-33	-37	-41	-45
10.8	Res Water Heater Eff.	0	0	-1	-1	-1	-1	-1	-2
20.0	Commercial	1,562	1,571	1,591	1,609	1,628	1,648	1,668	1,688
20.5	Com Standby Gen	-10	-10	-10	-10	-10	-10	-10	-10
30.0	Industrial	821	815	822	828	835	840	846	853
60.0	PSL	2	2	2	2	2	2	2	3
70.0	OPA	89	88	89	90	91	92	93	94
80.0	Company Use	31	31	31	32	32	32	32	32
92.0	Municipals	173	173	174	174	175	176	176	177
97.0	Cooperatives	.	.	.	.	.	.	.	.
98.7	EE Impact	0	0	-24	-50	-76	-102	-128	-155
99.1	Standby Gen	-25	-25	-25	-25	-25	-25	-25	-25
99.2	Interruptible Loads	-191	-192	-193	-194	-195	-196	-197	-198
		======	======	======	======	======	======	======	======
		4,589	4,619	4,650	4,675	4,685	4,709	4,734	4,759

xclass	desc	_2028	_2029	_2030	_2031	_2032	_2033	_2034
10.0	Residential	2,375	2,401	2,427	2,455	2,482	2,509	2,536
10.5	Res SEER	-49	-53	-56	-57	-58	-59	-60
10.8	Res Water Heater Eff.	-2	-2	-2	-2	-2	-2	-2
20.0	Commercial	1,707	1,726	1,744	1,764	1,784	1,803	1,822
20.5	Com Standby Gen	-10	-10	-10	-10	-10	-10	-10
30.0	Industrial	860	867	874	881	888	895	902
60.0	PSL	3	3	3	3	3	3	3
70.0	OPA	96	97	98	99	100	101	102
80.0	Company Use	33	33	33	33	33	34	34
92.0	Municipals	178	179	179	180	181	182	182
97.0	Cooperatives	.	.	.	.	.	.	.
98.7	EE Impact	-183	-211	-211	-211	-211	-211	-211
99.1	Standby Gen	-25	-25	-25	-25	-25	-25	-25
99.2	Interruptible Loads	-199	-200	-201	-202	-203	-204	-205
		======	======	======	======	======	======	======
		4,784	4,805	4,853	4,908	4,962	5,016	5,068

The following Table 5 has a description of each component in the forecast.

Table 5

Category		Description
10.0	Residential	Residential Base Load
10.5	Res SEER	Adjustment for Improved SEER Rating
10.8	Res Water Heater Eff.	Adjustment for Improved Water Heater Efficiency
20.0	Commercial	Commercial Base Load
20.5	Com Standby Gen	Retail Standby Generation
30.0	Industrial	Industrial Base Load
60.0	PSL	Public Street Lighting
70.0	OPA	Other Public Authorities
80.0	Company Use	Company Use
92.0	Municipals	Municipalities
97.0	Cooperatives	Cooperatives
98.7	EE Impact	Energy Efficiency Impacts from DSM Scenarios
99.1	Standby Gen	Wholesale Standby Generation
99.2	Interruptible Loads	Retail Interruptible Load

The following Table 6 shows all the components that comprise the winter peak demand forecast.

Table 6 - WINTER PEAK DEMAND FORECAST

xclass	desc	_2020	_2021	_2022	_2023	_2024	_2025	_2026	_2027
10.0	Residential	2,564	2,598	2,631	2,663	2,696	2,730	2,763	2,795
10.5	Res SEER	-12	-12	-14	-33	-37	-41	-45	-49
10.8	Res Water Heater Eff.	-2	-4	-4	-5	-5	-6	-6	-7
20.0	Commercial	1,358	1,375	1,391	1,408	1,424	1,442	1,459	1,476
20.5	Com Standby Gen	-10	-10	-10	-10	-10	-10	-10	-10
30.0	Industrial	704	710	716	721	726	731	737	743
60.0	PSL	3	3	3	3	3	3	3	3
70.0	OPA	72	73	74	74	75	76	77	78
80.0	Company Use	31	32	32	32	32	32	33	33
92.0	Municipals	172	172	173	173	174	175	175	176
97.0	Cooperatives	.	.	.	.	.	.	.	.
98.7	EE Impact	0	-24	-48	-74	-97	-121	-147	-173
99.1	Standby Gen	-25	-25	-25	-25	-25	-25	-25	-25
99.2	Interruptible Loads	-188	-190	-192	-194	-198	-203	-213	-225
		======	======	======	======	======	======	======	======
		4,667	4,698	4,727	4,733	4,758	4,782	4,802	4,815

xclass	desc	_2028	_2029	_2030	_2031	_2032	_2033	_2034
10.0	Residential	2,827	2,857	2,890	2,922	2,954	2,985	3,016
10.5	Res SEER	-53	-55	-56	-57	-58	-59	-60
10.8	Res Water Heater Eff.	-7	-8	-8	-8	-8	-8	-8
20.0	Commercial	1,492	1,508	1,525	1,542	1,558	1,575	1,591
20.5	Com Standby Gen	-10	-10	-10	-10	-10	-10	-10
30.0	Industrial	749	755	761	767	772	779	785
60.0	PSL	3	3	3	3	3	3	3
70.0	OPA	79	80	81	82	82	83	84
80.0	Company Use	33	33	33	34	34	34	34
92.0	Municipals	177	177	178	179	180	181	181
97.0	Cooperatives	.	.	.	.	.	.	.
98.7	EE Impact	-199	-199	-199	-199	-199	-199	-199
99.1	Standby Gen	-25	-25	-25	-25	-25	-25	-25
99.2	Interruptible Loads	-239	-240	-241	-242	-243	-244	-245
		======	======	======	======	======	======	======
		4,826	4,875	4,931	4,987	5,039	5,094	5,146

Customer and Sales Growth Comparisons: History and Forecast

The following table, Table 7, shows the growth in customers and sales over the last five years and that projected over the next five years. The variable or header labeled “hisgr” is the compound average annual growth rate for the five years 2014 through 2019 and the variable “forgr” is the growth rate for the five-year period 2020 through 2025. For the residential class, the number of customers is the driver for growth in residential peak demand. The table shows that the projected growth over the next five years is only slightly lower than over the previous five years, i.e., 1.0% versus 1.1%. Similarly, for the commercial class of customers, the projected growth rate is only slightly lower than the historical rate, -0.1% versus 0.1%. While not affecting the peak demand forecast, the weather normalized average kWh per customer for the residential customers is expected to continue declining over the next five years but at a slower rate than in the last five years while for commercial customers, the decline is slightly faster. Industrial GWH sales are expected to increase over the next five years. The decrease in industrial sales over the last five years is, to a large extent, the result of the loss of several large customers.

Table 7 – Customers and Weather Normalized Sales Over +/- 5 Years

CLASS=Residential

Obs	desc	_2014	_2019	_2020	_2025	hisgr	forgr
1	Nbr Customers	587856	636386	645797	688741	1.6	1.3
2	kWh per Customer	13,167	12,843	12,623	12,410	-0.5	-0.3
3	Total GWH Sales	7,741	8,173	8,152	8,547	1.1	1.0

CLASS=Commercial

Obs	desc	_2014	_2019	_2020	_2025	hisgr	forgr
4	Nbr Customers	91,952	97,544	98,185	103547	1.2	1.1
5	kWh per Customer	79,116	75,137	75,134	70,929	-1.0	-1.1
6	Total GWH Sales	7,275	7,329	7,377	7,344	0.1	-0.1

CLASS=Industrial

Obs	desc	_2014	_2019	_2020	_2025	hisgr	forgr
7	Total GWH Sales	6,234	5,694	5,812	6,090	-1.8	0.9

CLASS=All_Sales

Obs	desc	_2014	_2019	_2020	_2025	hisgr	forgr
8	Total GWH Sales	22,769	22,661	22,803	22,953	-0.1	0.1

The following table, Table 8, contains similar information on a 15-year basis, which also reflects a similar result.

Table 8 – Customers and Weather Normalized Sales Over +/- 15 Years

CLASS=Residential

Obs	desc	_2004	_2019	_2020	_2034	hisgr	forgr
1	Nbr Customers	492197	636386	645797	762544	1.7	1.2
2	kWh per Customer	15,056	12,843	12,623	12,787	-1.1	0.1
3	Total GWH Sales	7,411	8,173	8,152	9,751	0.7	1.3

CLASS=Commercial

Obs	desc	_2004	_2019	_2020	_2034	hisgr	forgr
4	Nbr Customers	80,739	97,544	98,185	114483	1.3	1.1
5	kWh per Customer	85,788	75,137	75,134	64,278	-0.9	-1.1
6	Total GWH Sales	6,926	7,329	7,377	7,359	0.4	-0.0

CLASS=Industrial

Obs	desc	_2004	_2019	_2020	_2034	hisgr	forgr
7	Total GWH Sales	6,780	5,694	5,812	6,587	-1.2	0.9

CLASS=All_Sales

Obs	desc	_2004	_2019	_2020	_2034	hisgr	forgr
8	Total GWH Sales	23,163	22,661	22,803	24,309	-0.1	0.5

APPENDIX

Figure A1a: Components Of 2025 and 2030 Summer Peak Demand Forecast

			Energy Forecast		Summer Peak		
yr	class	desc	Customer	GWH Sales	kW Per	Factor	Peak Demand
2025	10.0	Res	688,741	.	3.294	1.0099	2,290
	10.2	Res.Adj	.	.	.	.	-38
	20.0	Com	103,547	.	15.757	1.0099	1,648
	30.0	Ind	.	6090.4	0.915	1.0099	642
	30.1	Ind.DR	.	.	.	.	198
	60.0	PSL	.	166.7	0.127	1.0099	2
	70.0	OPA	.	540.2	1.481	1.0099	92
	92.0	Muni	.	882.9	1.727	1.0099	176
	98.1	CoUse	.	.	.	.	32
	98.5	DR	.	.	.	.	-231
	98.7	EE	.	.	.	.	-102
2025			.	.	.	.	4,709

			Energy Forecast		Summer Peak		
yr	class	desc	Customer	GWH Sales	kW Per	Factor	Peak Demand
2030	10.0	Res	729,902	.	3.294	1.0099	2,427
	10.2	Res.Adj	.	.	.	.	-58
	20.0	Com	109,612	.	15.757	1.0099	1,744
	30.0	Ind	.	6359.6	0.915	1.0099	671
	30.1	Ind.DR	.	.	.	.	203
	60.0	PSL	.	178.8	0.127	1.0099	3
	70.0	OPA	.	572.1	1.481	1.0099	98
	92.0	Muni	.	900.3	1.727	1.0099	179
	98.1	CoUse	.	.	.	.	33
	98.5	DR	.	.	.	.	-236
	98.7	EE	.	.	.	.	-211
2030			.	.	.	.	4,853

Figure A1b: Components 0f 2025/2026 and 2030/2031 Winter Peak Demand Forecast

				Energy Forecast		Winter Peak	
wyr	yr	class	desc	Customer	GWH Sales	kW Per	Peak Demand
2025	2026	10.0	Res	697,362	.	3.916	2,730
		10.2	Res.Adj	.	.	.	-47
		20.0	Com	104,806	.	13.756	1,442
		30.0	Ind	.	6137.9	0.768	538
		30.1	Ind.DR	.	.	.	193
		60.0	PSL	.	169.0	0.155	3
		70.0	OPA	.	546.6	1.220	76
		92.0	Muni	.	886.3	1.726	175
		98.1	CoUse	.	.	.	32
		98.5	DR	.	.	.	-238
		98.7	EE	.	.	.	-121
2025	2026			.	.	.	4,782

				Energy Forecast		Winter Peak	
wyr	yr	class	desc	Customer	GWH Sales	kW Per	Peak Demand
2030	2031	10.0	Res	738,190	.	3.916	2,890
		10.2	Res.Adj	.	.	.	-64
		20.0	Com	110,853	.	13.756	1,525
		30.0	Ind	.	6416.5	0.768	563
		30.1	Ind.DR	.	.	.	198
		60.0	PSL	.	181.4	0.155	3
		70.0	OPA	.	579.1	1.220	81
		92.0	Muni	.	903.9	1.726	178
		98.1	CoUse	.	.	.	33
		98.5	DR	.	.	.	-276
		98.7	EE	.	.	.	-199
2030	2031			.	.	.	4,931

Concerning Figures A2-A13

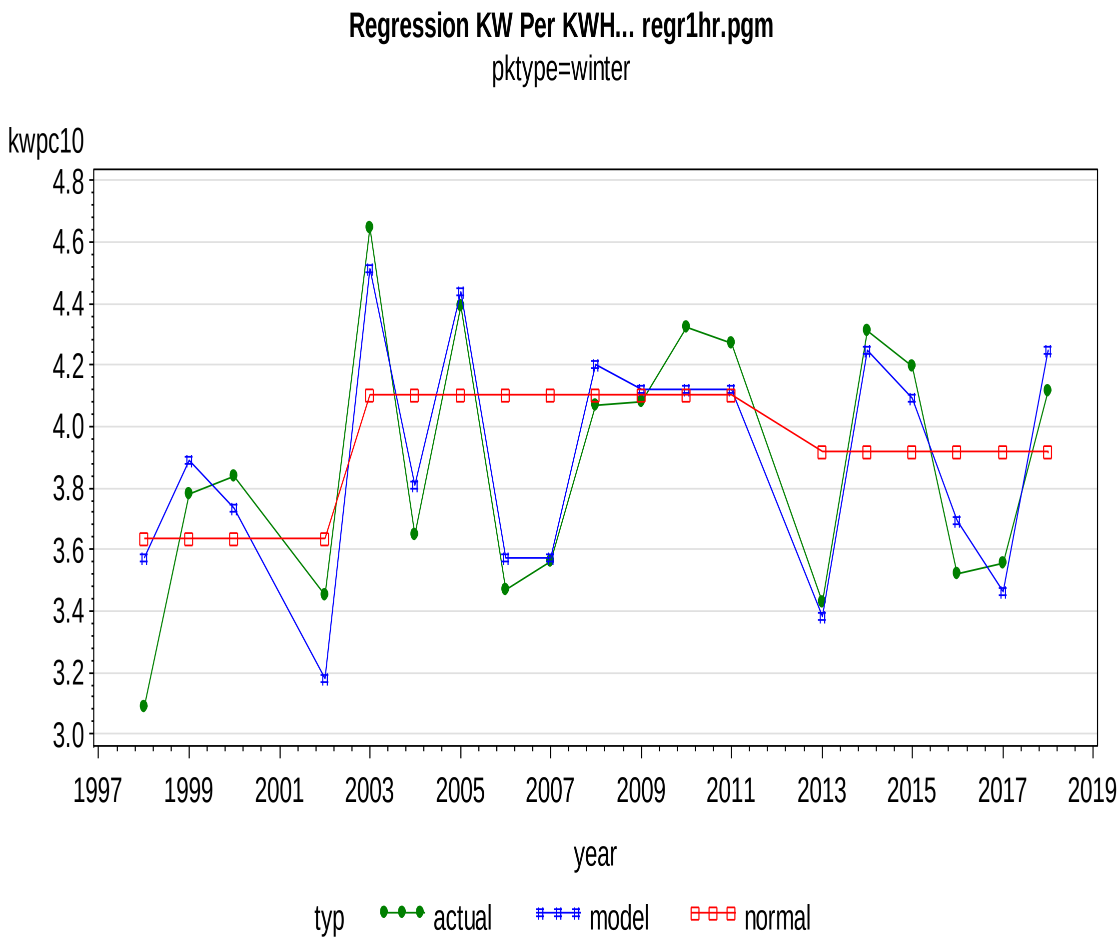
Figures A2-A13 show the results of an "Analysis of Variance" approach to the changes in kW per customer or kW per kWh for each of the classes of customer, i.e. an ANOVA model. When weather is a statistically significant factor in the variation of peak contribution, an "Analysis of Covariance" is used, i.e. an ANCOVA model. Figures A2-A7 show results for the winter and Figures A8-A13, for the summer. The customer classes are: residential, commercial, industrial, public street lighting, other public authorities, and municipalities.

The fixed effects variables are 0-1 dummy variables where the start and stop year, i.e. the years when the variable equals one, are indicated in the name of the variable. For example, in Figure A2 showing results for the residential class in winter, the variable "i03_11", takes on the value 1 in the years 2003 through 2011 and 0 elsewhere.

The weather variables for the peak day used in the models are:

Mntmp=minimum daily temperature;
Hdh60 = heating degree hours base 60;
Cdh = cooling degree hours base 75; and
Maxtmp=maximum daily temperature.

Figure A2: Residential Winter kW per Customer Regression Equation



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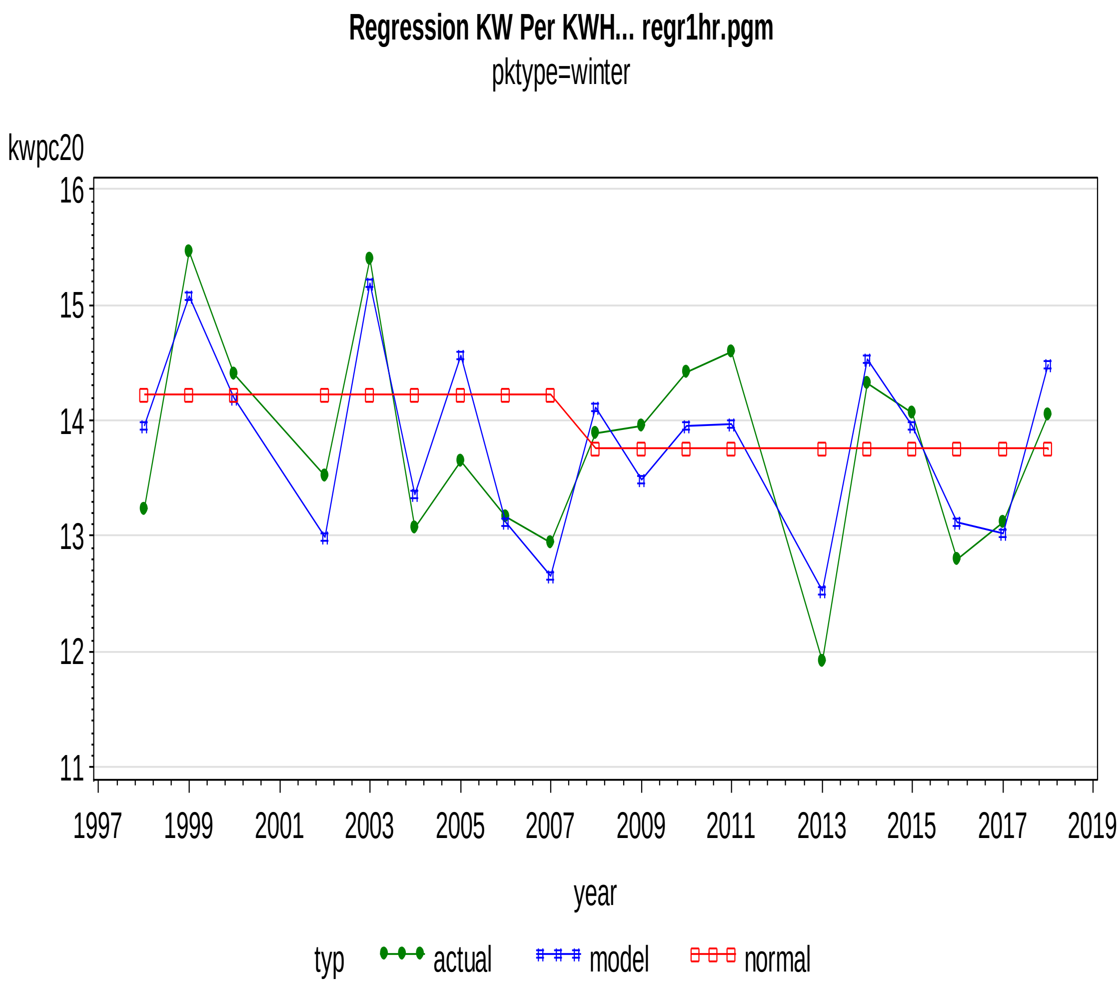
Root MSE	0.16681	R-Square	0.8538
Dependent Mean	3.90635	Adj R-Sq	0.8245
Coeff Var	4.27020		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	5.50436	0.20909	26.32	<.0001	0
i98_02	1	-0.27949	0.11368	-2.46	0.0266	1.27701
i03_11	1	0.18896	0.08792	2.15	0.0483	1.27515
mntmp	1	-0.07860	0.00941	-8.35	<.0001	1.00166

Figure A3: Commercial Winter kW per Customer Regression Equation

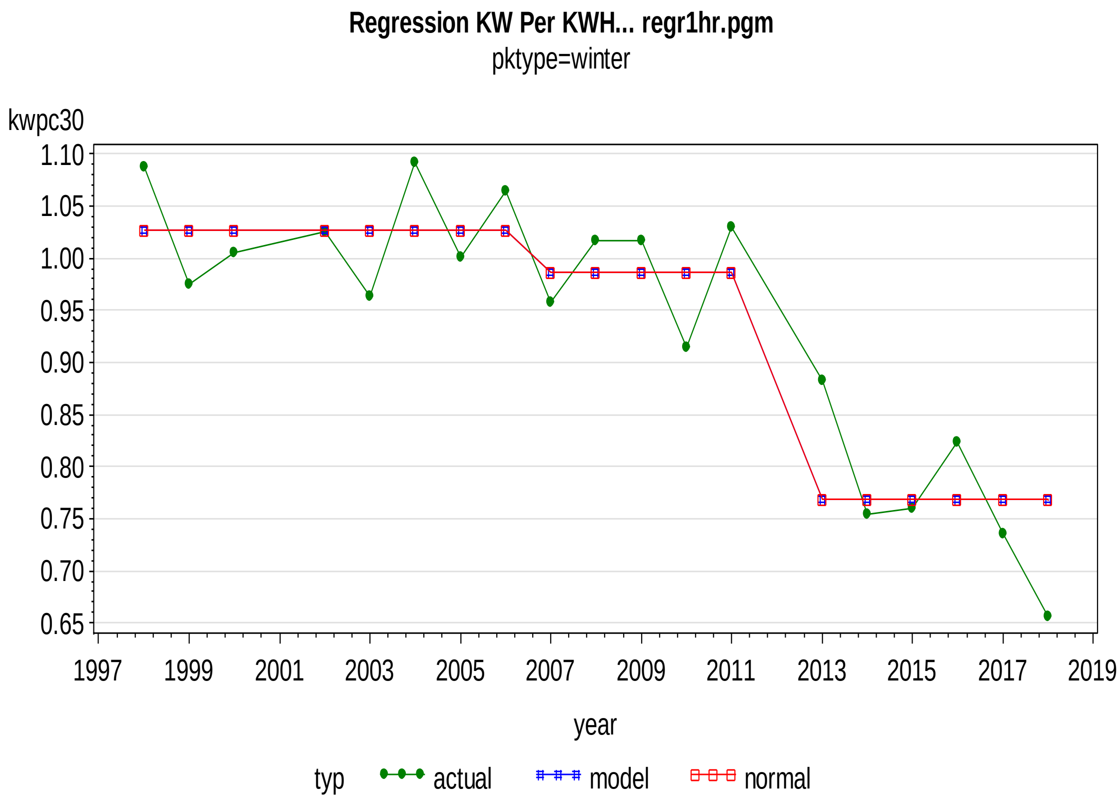


Root MSE	0.46150	R-Square	0.7594
Dependent Mean	13.79151	Adj R-Sq	0.7293
Coeff Var	3.34630		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	6.77158	0.99359	6.82	<.0001	0
i98_07	1	0.47607	0.21827	2.18	0.0444	1.04157
hdh60	1	0.02322	0.00329	7.06	<.0001	1.04157

Figure A4: Industrial Winter kW per kWh Regression Equation

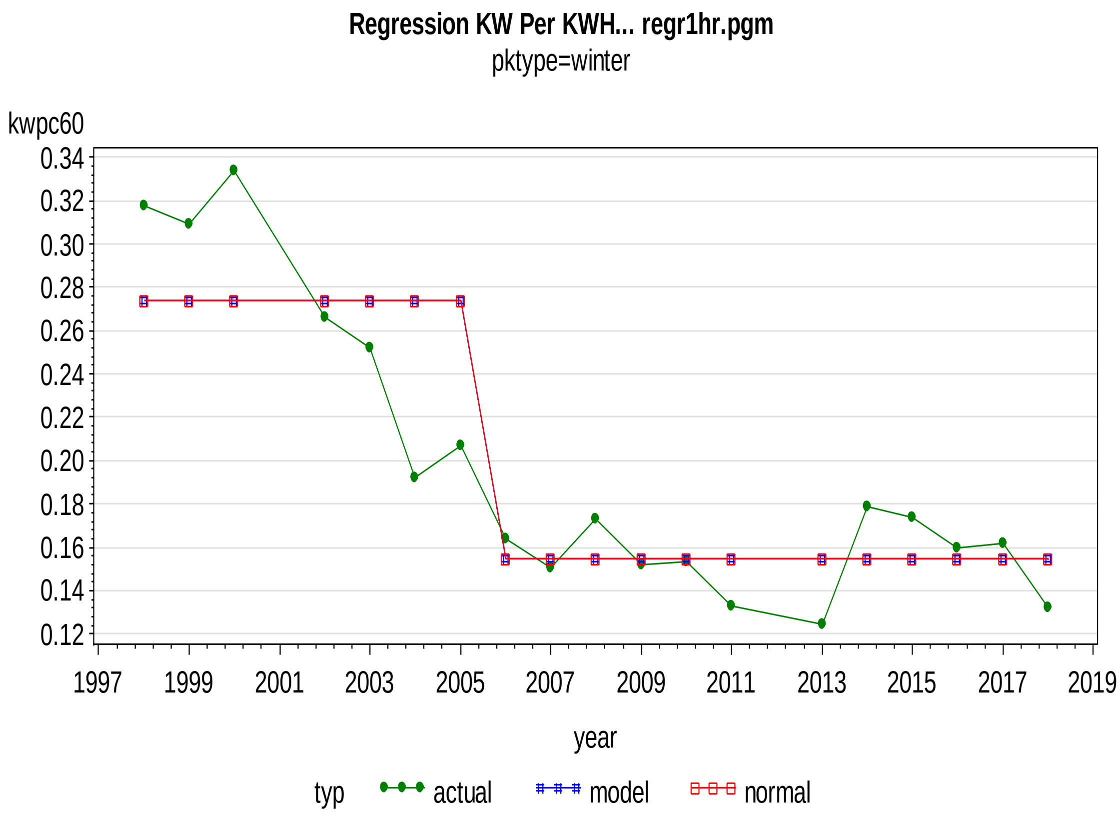


Root MSE	0.05622	R-Square	0.8214
Dependent Mean	0.93929	Adj R-Sq	0.7991
Coeff Var	5.98494		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	0.76844	0.02400	32.02	<.0001	0
i98_06	1	0.25826	0.03116	8.29	<.0001	1.39441
i07_11	1	0.21844	0.03476	6.28	<.0001	1.39441

Figure A5: Public Street Lighting Winter kW per kWh Regression Equation

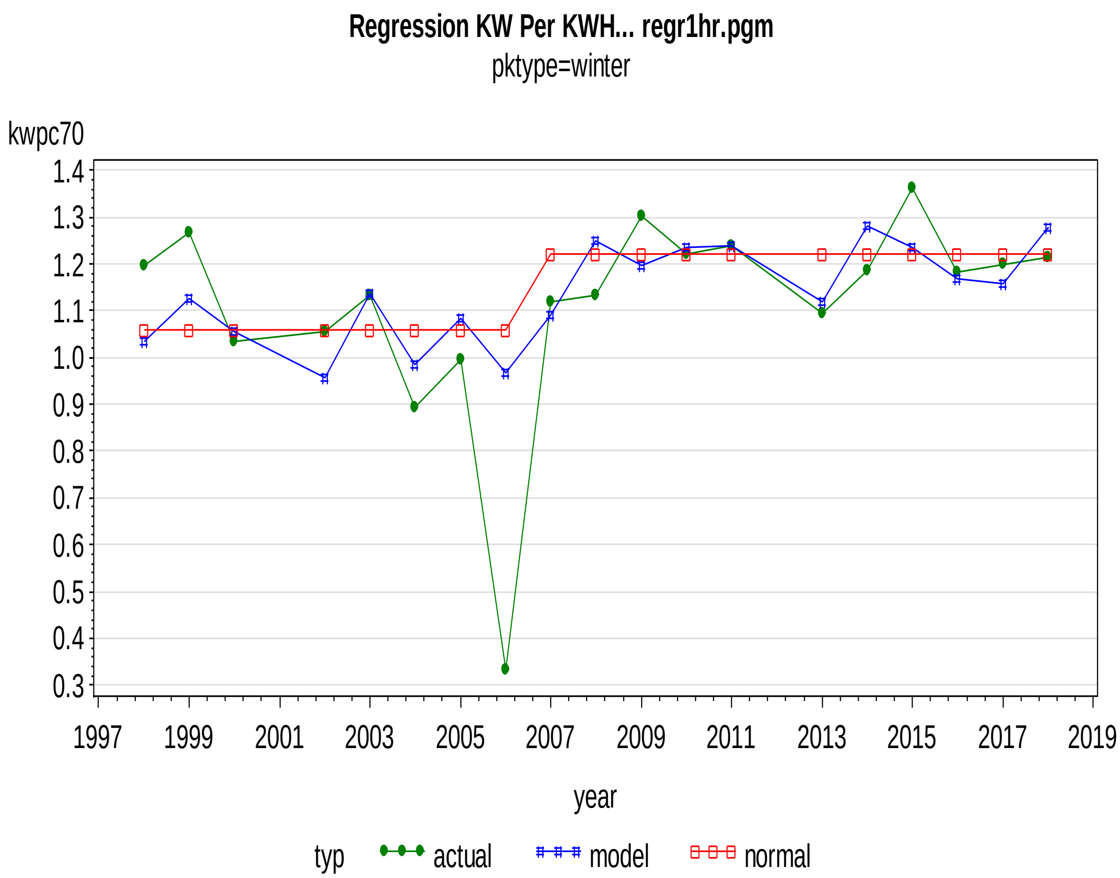


Root MSE	0.03172	R-Square	0.7719
Dependent Mean	0.19499	Adj R-Sq	0.7585
Coeff Var	16.26903		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	0.15462	0.00916	16.88	<.0001	0
i98_05	1	0.11950	0.01576	7.58	<.0001	1.00000

Figure A6: Other Public Authorities Winter kW per kWh Regression Equation

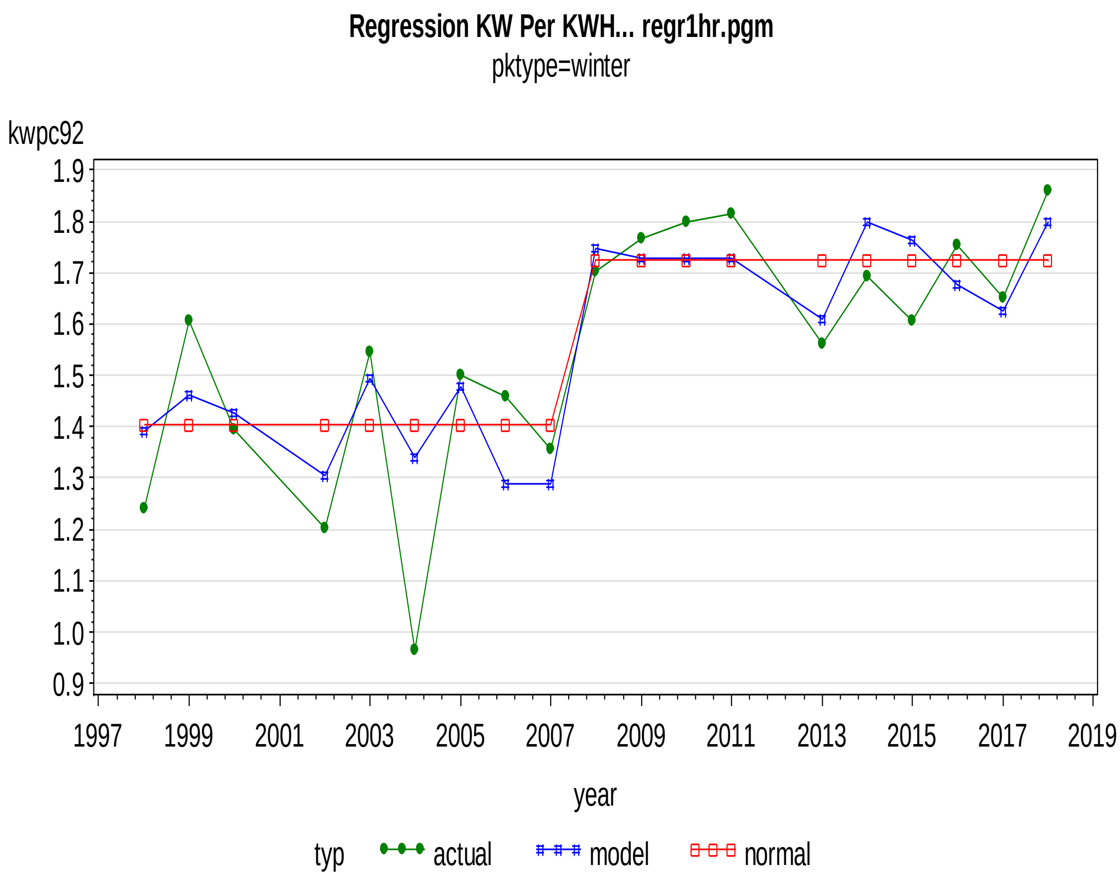


Root MSE	0.12596	R-Square	0.4073
Dependent Mean	1.14332	Adj R-Sq	0.3332
Coeff Var	11.01711		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	0.64802	0.26746	2.42	0.0276	0
i98_06	1	-0.16172	0.06022	-2.69	0.0162	1.00363
hdh60	1	0.00190	0.00090387	2.10	0.0516	1.00363

Figure A7: Municipal Winter kW per kWh Regression Equation



Root MSE	0.11432	R-Square	0.7369
Dependent Mean	1.57032	Adj R-Sq	0.7040
Coeff Var	7.28016		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	2.07578	0.13884	14.95	<.0001	0
i98_07	1	-0.32053	0.05385	-5.95	<.0001	1.00464
mntmp	1	-0.01732	0.00653	-2.65	0.0174	1.00464

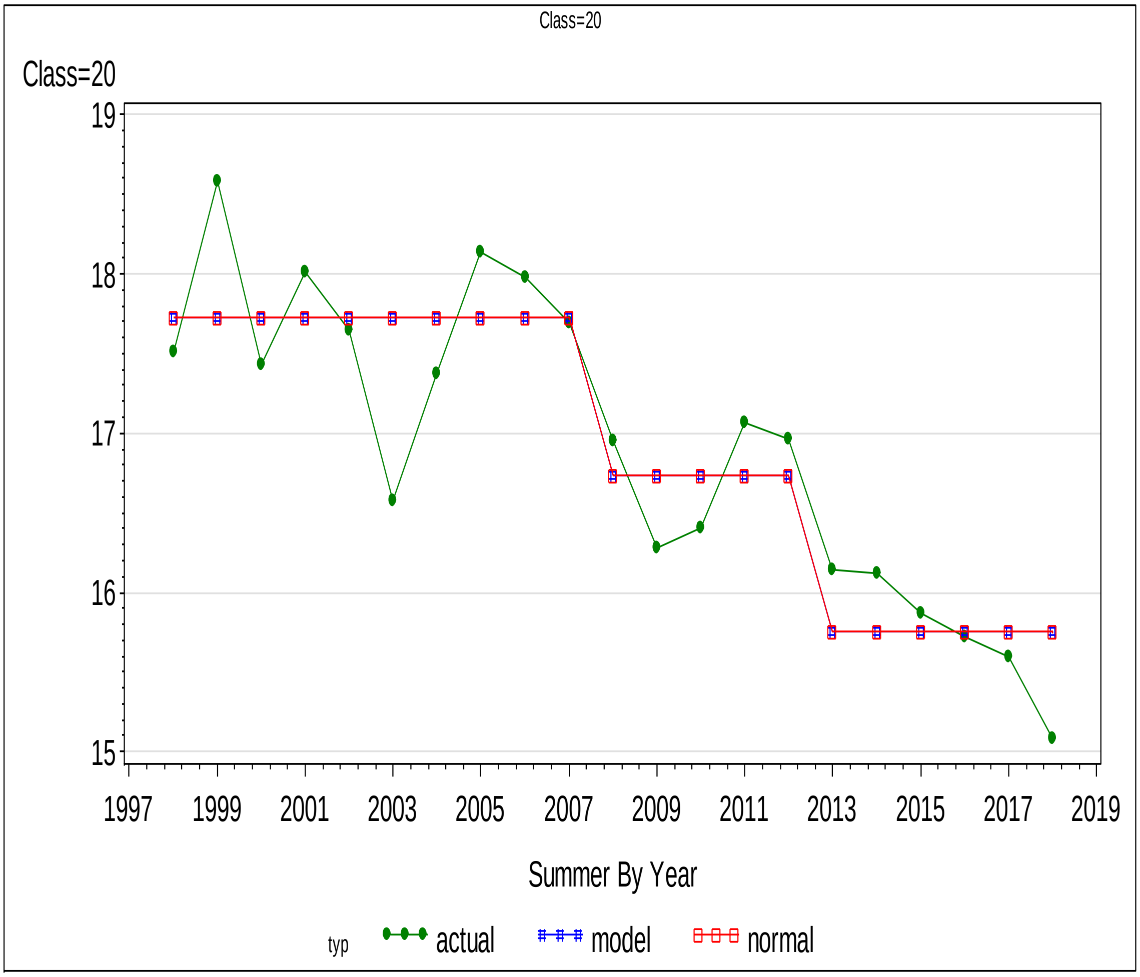
Figure A8: Residential Summer kW per Customer Regression Equation

Root MSE	0.05206	R-Square	0.9643
Dependent Mean	3.61923	Adj R-Sq	0.9554
Coeff Var	1.43845		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	2.41840	0.13554	17.84	<.0001	0
i98_04	1	0.45984	0.03009	15.28	<.0001	1.50864
i05_08	1	0.54877	0.03536	15.52	<.0001	1.48789
i09_12	1	0.28135	0.03387	8.31	<.0001	1.36511
cdh	1	0.00497	0.00074092	6.71	<.0001	1.31388

Figure A9: Commercial Summer kW per Customer Regression Equation

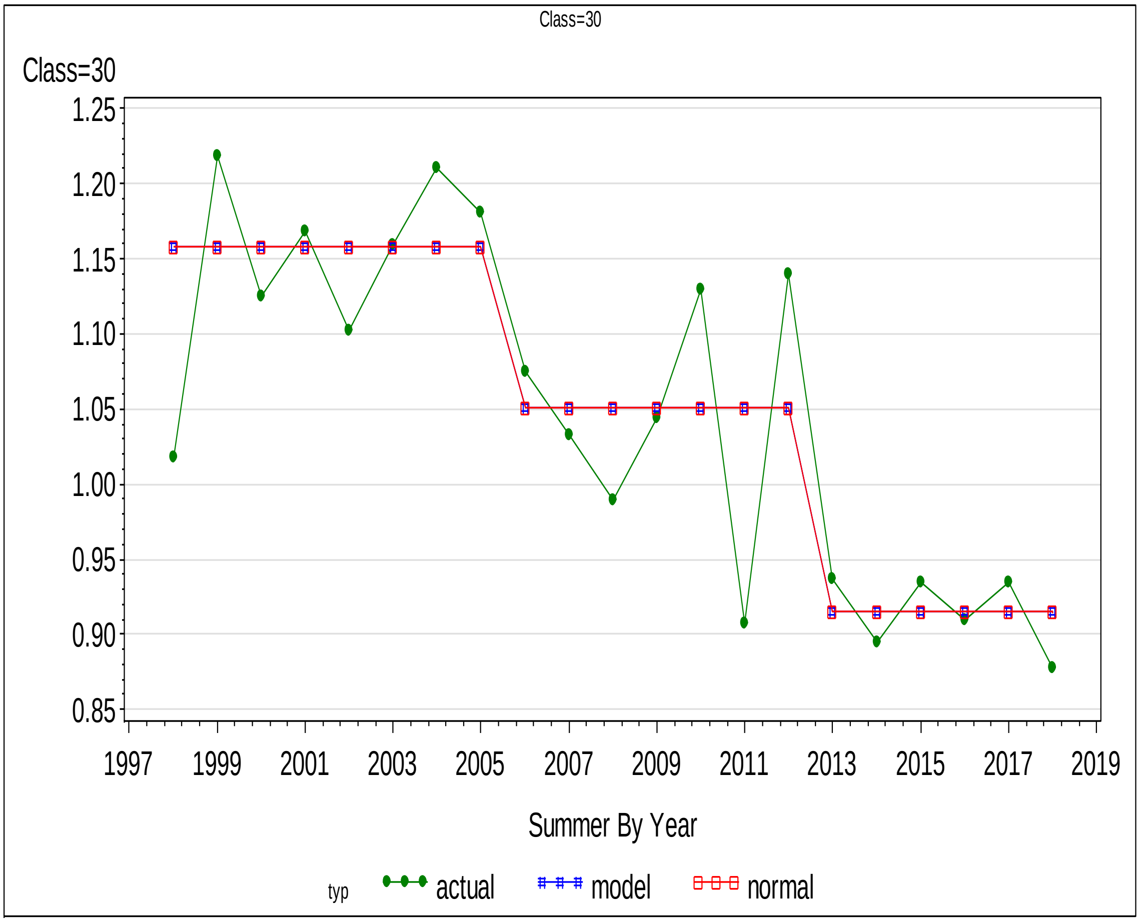


Root MSE	0.42011	R-Square	0.8180
Dependent Mean	16.90169	Adj R-Sq	0.7977
Coeff Var	2.48561		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	15.75675	0.17200	91.61	<.0001	0
i98_07	1	1.96759	0.22024	8.93	<.0001	1.38519
i08_12	1	0.97650	0.25472	3.83	0.0012	1.38519

Figure A10: Industrial Summer kW per kWh Regression Equation

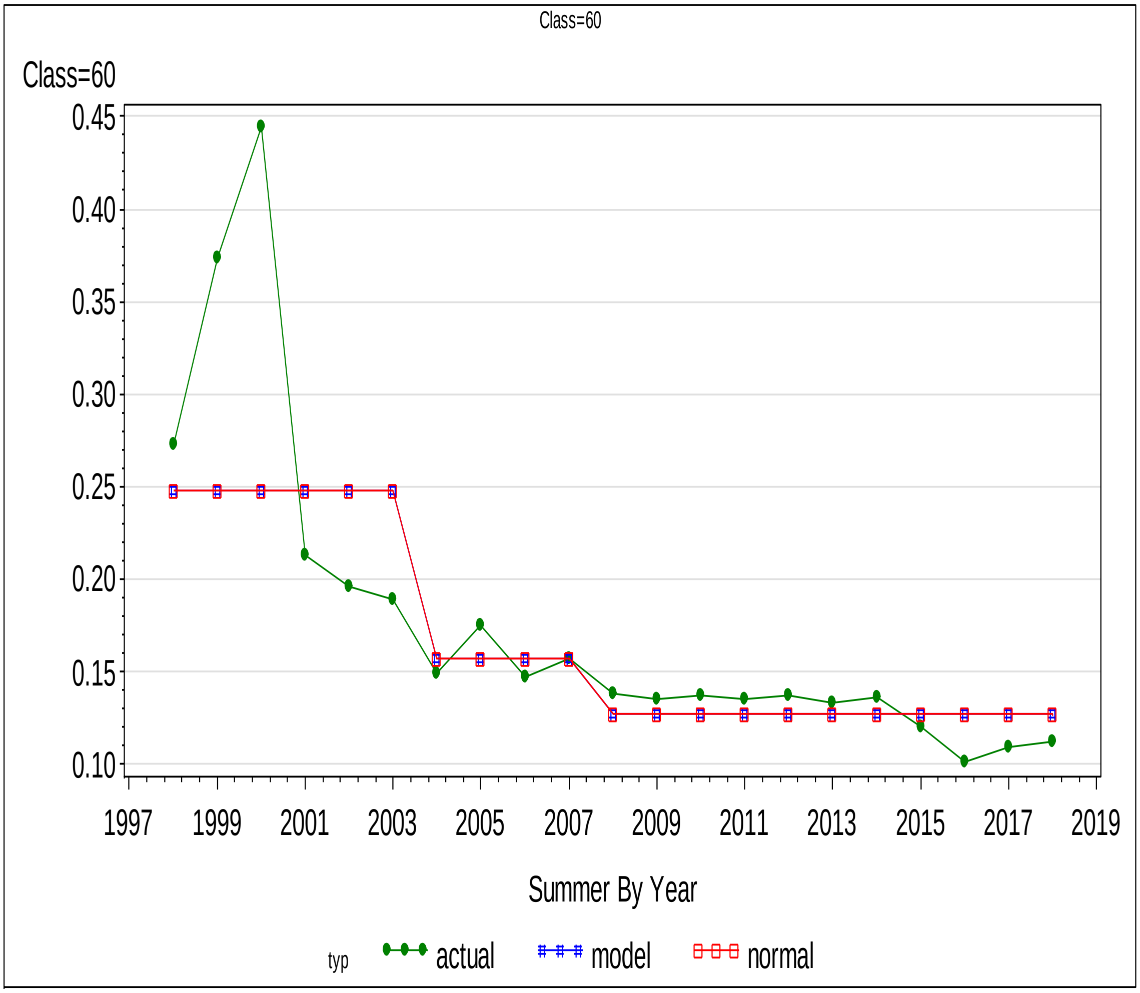


Root MSE	0.04873	R-Square	0.8197
Dependent Mean	1.04868	Adj R-Sq	0.7997
Coeff Var	4.64670		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	1.05038	0.02065	50.88	<.0001	0
i98_05	1	0.10751	0.02744	3.92	0.0010	1.41561
i13_18	1	-0.13563	0.02867	-4.73	0.0002	1.41561

Figure A11: Public Street Lighting Summer kW per kWh Regression Equation

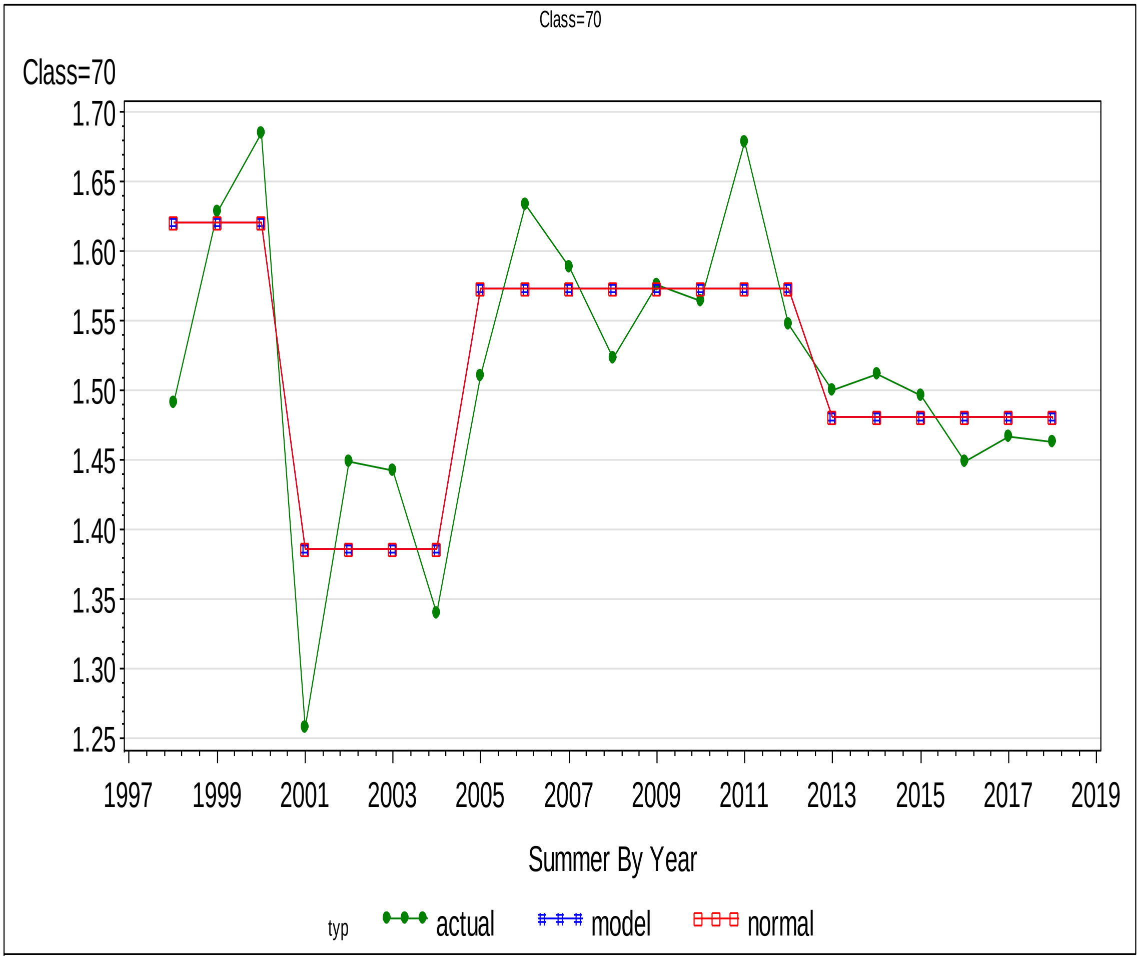


Root MSE	0.02845	R-Square	0.7002
Dependent Mean	0.15343	Adj R-Sq	0.6669
Coeff Var	18.54235		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	0.12674	0.00859	14.75	<.0001	0
i98_03	1	0.12075	0.01864	6.48	<.0001	1.06023
i04_07	1	0.03028	0.01662	1.82	0.0851	1.06023

Figure A12: Other Public Authorities Summer kW per kWh Regression Equation

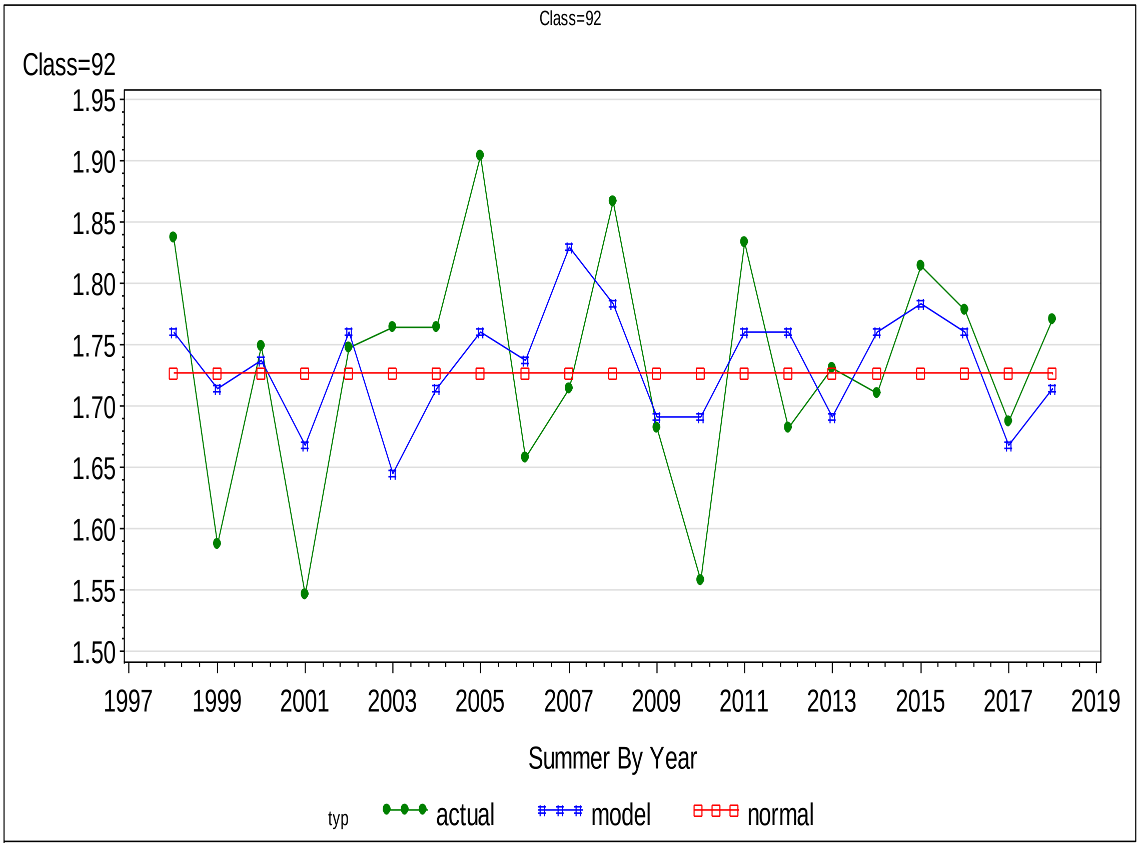


Root MSE	0.05624	R-Square	0.6909
Dependent Mean	1.51832	Adj R-Sq	0.6363
Coeff Var	3.70412		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	1.48147	0.02296	64.52	<.0001	0
i98_00	1	0.13919	0.04201	3.31	0.0041	1.24186
i01_04	1	-0.09463	0.03763	-2.51	0.0223	1.30671
i05_12	1	0.09247	0.03064	3.02	0.0078	1.39548

Figure A13: Municipal Summer kW per kWh Regression Equation



Root MSE	0.08559	R-Square	0.2318
Dependent Mean	1.73295	Adj R-Sq	0.1913
Coeff Var	4.93871		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	-0.51862	0.94059	-0.55	0.5878	0
maxtmp	1	0.02302	0.00961	2.39	0.0271	1.00000

2018 Reserve Margin Study (Updated)

Summary

Dominion Energy South Carolina, Inc.'s ("DESC") reserve margin policy is summarized in the following table.

DESC's Reserve Margin Policy		
	Summer	Winter
Base Reserves	12%	14%
Peaking Reserves	14%	21%
Increment for Peaking	2%	7%

The analysis contained in this study reflects that a summer peaking reserve margin of 14.3% and a winter peaking reserve margin of 20.2% is appropriate for DESC and these results support the existing reserve margin policy. Also, the analysis for the base level of reserves to support operation of the system throughout the year outside of seasonal peaking periods reflects that a reserve level of 13.4% in summer and 14.9% in winter is appropriate for DESC. These results also support DESC's existing reserve policy and therefore DESC will maintain the base levels of reserve margin at 12% and 14% in summer and winter respectively.

Introduction

All electric utilities require supply reserves to mitigate the risk of not being able to serve their load requirement because of demand-side related risk and supply-side related risk. Demand-side risk results from uncertainty in the level of demand which can increase because of abnormal weather or other unforeseen circumstances. Supply-side risk results from the possibility of supply resources either not being available at all or their capacity being reduced because of mechanical, fuel, weather or other circumstances. DESC is also required to carry operating reserves sufficient to meet its VACAR reserve sharing agreement. While DESC's share of the VACAR reserves can change each year, it is typically within a few megawatts of 200 MW which is the amount DESC uses in its planning.

Reserve Margin Components
1. VACAR Operating Reserves 2. Demand-Side Risk 3. Supply-Side Risk

In determining its required reserve margin, it is necessary for DESC to analyze the need separately for the cooling season and the heating season. Additionally, within each season it is necessary to distinguish between a peaking need and a base need. There are at least two reasons for this. First, very cold weather can make DESC's winter peak spike for an hour or two. A peak clipping resource available for a few hours may be better suited to address this risk than a generating unit. Second, DESC anticipates a significant amount of solar capacity in its resource portfolio and the ability of solar to serve load can be substantially different during peak summer conditions as opposed to other times during the year.

<u>Demand-Side Risk</u>

The major source of demand-side risk derives from abnormal weather. To quantify the impact of weather on daily peak demands, a regression study was performed for each season separately. Three years of data were combined using the months of June, July, and August for the summer model and December 16 through March 16 for the winter model. The regression study followed the following steps for each season:

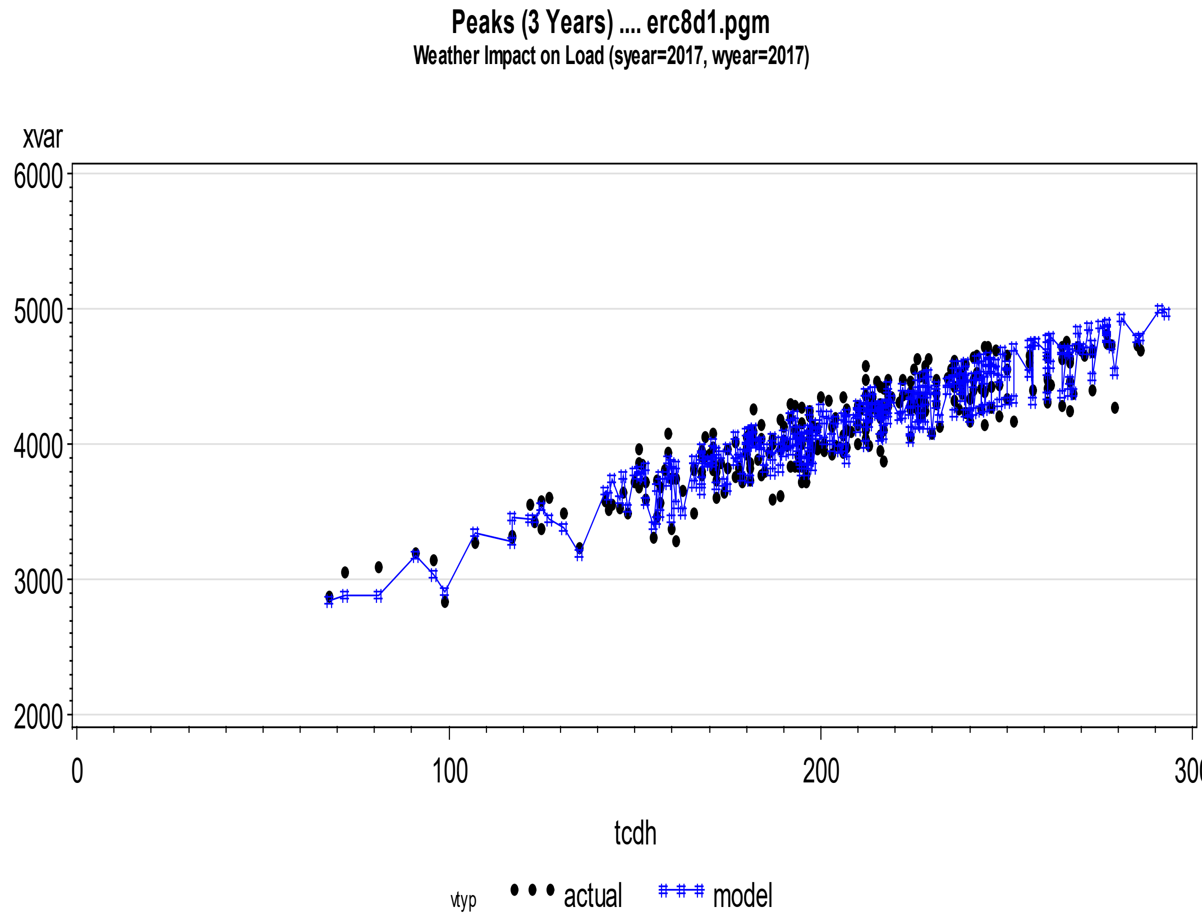
1. Define a set of explanatory variables such as cooling degree hours ("CDH") for summer and heating degree hours for winter ("HDH"). The square of these weather variables was added to the possible choices in case a quadratic equation provided the best fit. To avoid collinearity problems between the linear and squared terms, the deviation from the mean value of both CDH and HDH was used instead of the actual degree hours.
2. The stepwise model selection procedure in SAS[1] was used to find the best set of explanatory variables to use in the regression equation to explain variations in daily peak demand. The stepwise procedure will add or subtract a variable to build the best regression model in terms of goodness of fit. A variable is added to the equation if it meets a specified significance level when added. After adding a variable, the stepwise procedure checks all the variables presently in the regression equation to make sure they meet a certain significance level to stay in the equation. A statistical significance level of 15% was used for both adding a variable and removing a variable. The SAS code that implements this procedure is shown in the appendix with the list of explanatory variables provided.
3. The best model specification chosen by the stepwise procedure was estimated first using a robust regression procedure to identify outliers in the data which are assigned appropriate weights by the modeling procedure. The final estimation of the model was made in a

[1] SAS is a computer programming language used widely in industry to do analytics.

weighted regression analysis using those weights. This mitigated any bias from the squared residuals associated with outliers.

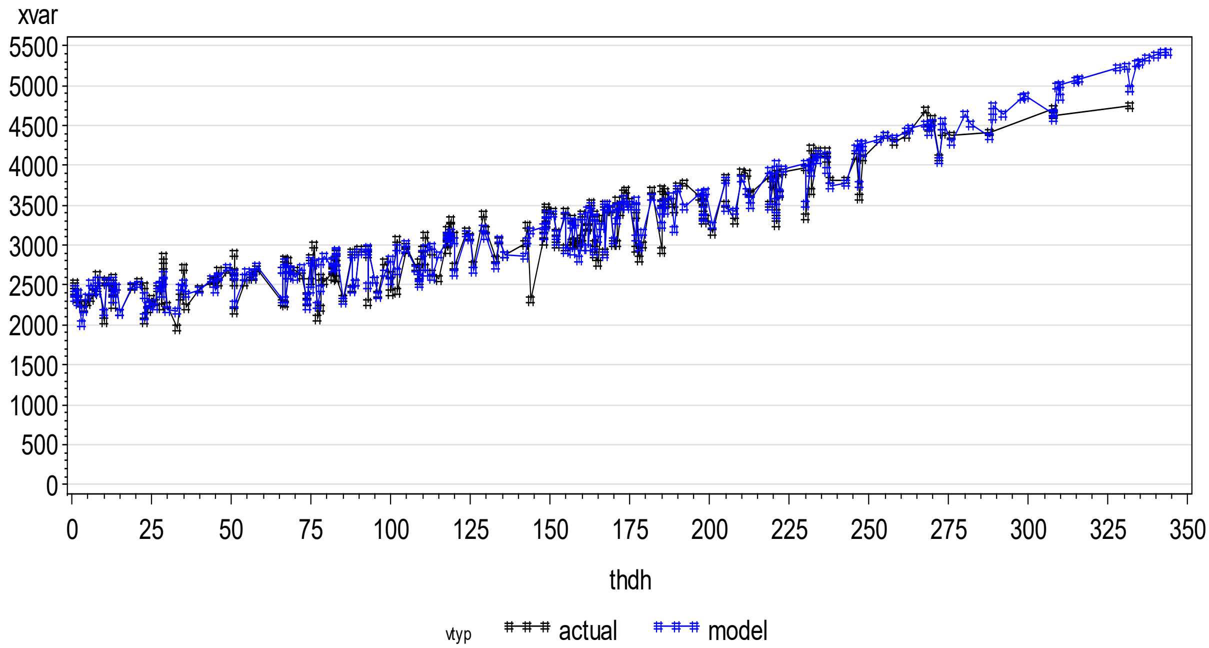
4. The above was first performed for all the days in the summer season for which CDH was greater than zero and in the winter season for which HDH was greater than zero. To estimate a sensitivity to the data, the entire process was repeated using the 100 hottest days in summer based on CDH and the coldest 100 days in winter based on HDH.
5. The stepwise procedure chose a quadratic formulation as the best fitting model in summer and winter with all the days used and in winter with only the 100 coldest days. Stepwise chose a linear model in summer when only the 100 hottest days were used. To complete all the combinations, Stepwise was forced to estimate a linear model in winter and a quadratic model in summer using the extreme 100 days. Thus, DESC estimated three summer models and three winter models.
6. The seasonal peak demand days on the system since 1991 were identified and the weather from those days as well as day of week and month of occurrence were entered into the six regression equations to estimate what the seasonal peak demand would be today if the historical peak conditions were present. For each season, approximately 28 different peak demands were calculated. The average of these seasonal peaks was taken as an approximation of the peak demand under normal weather conditions and the difference between the maximum and the normal represents the seasonal demand side risk, which is the goal of this exercise.

The following chart compares the summer regression model's daily peak estimates to the actual daily peak demands. The estimated regression equations and related statistics are included as appendices.

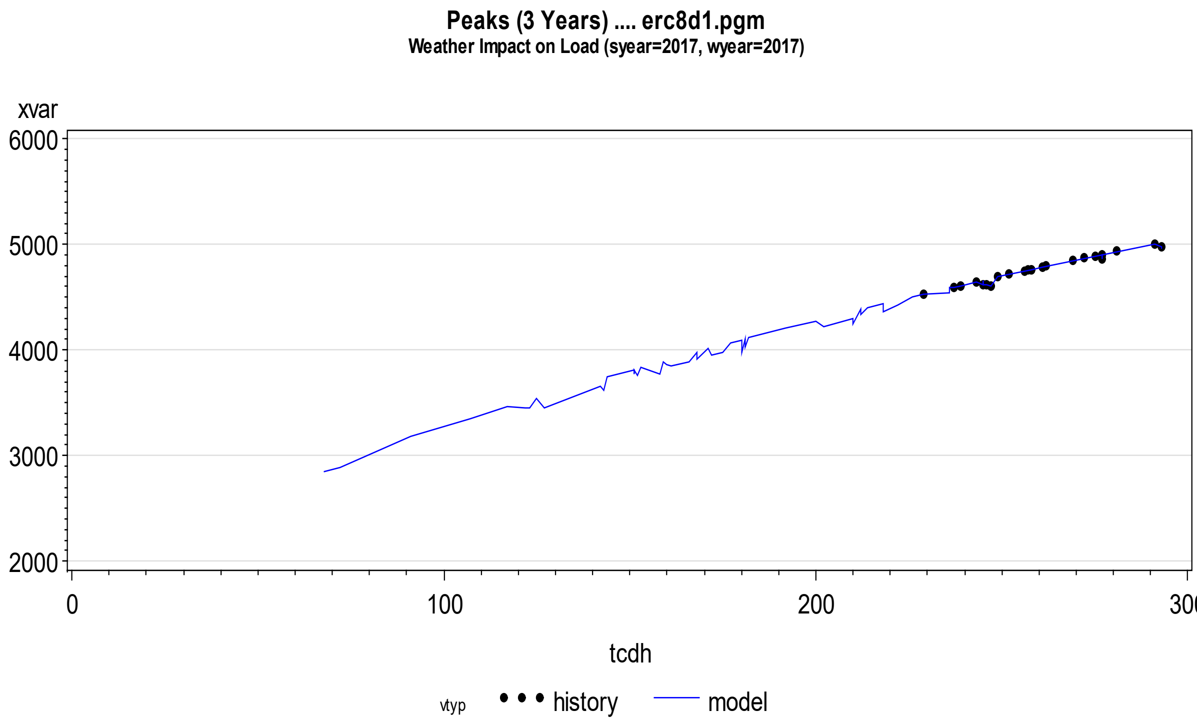


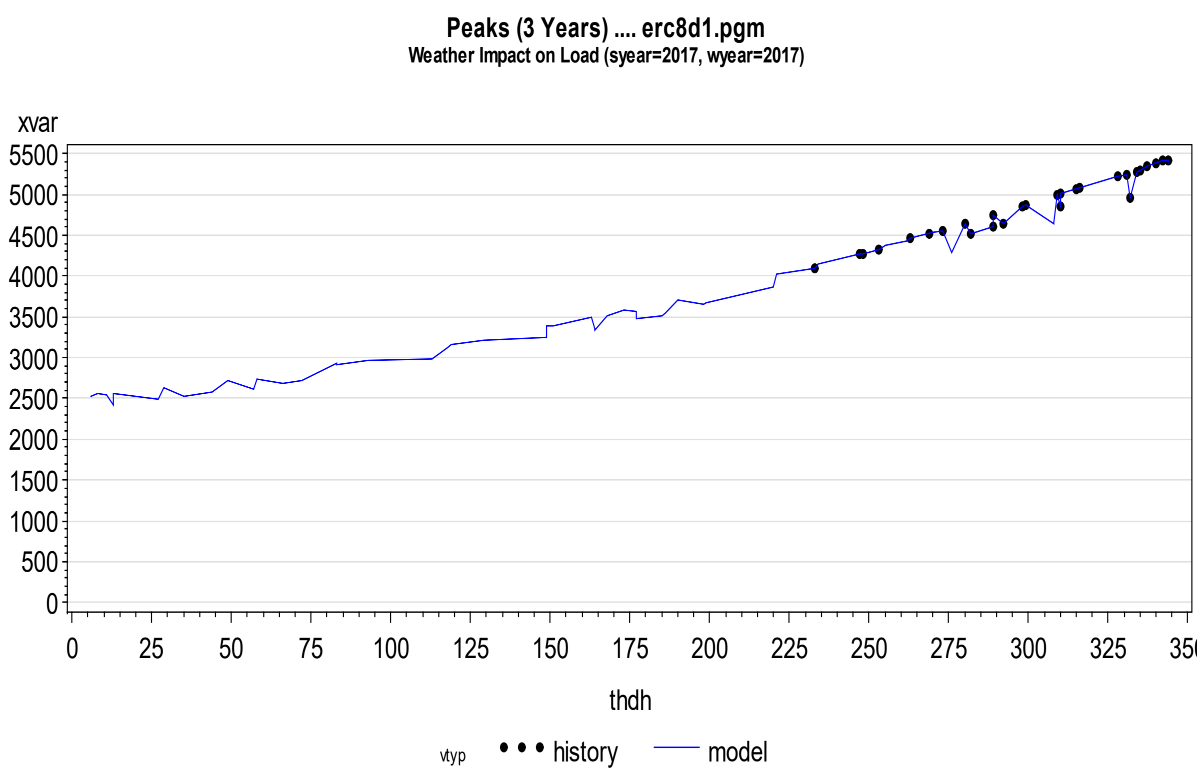
The following chart compares the winter regression model's daily peak estimates to the actual daily peak demands.

Peaks (3 Years) erc8d1.pgm
Weather Impact on Load (syear=2017, wyear=2017)



The next step used these regression equations to estimate what the peak demand would be on DESC's system today given the weather that occurred on historical peak days since 1991. The following two charts display the regression equation, the resulting peak demands and where they fall along the regression line. The first chart is for the summer season and the second for the winter season.


Peaks (3 Years) erc8d1.pgm
Weather Impact on Load (syear=2017, wyear=2017)
xvar
6000
5000
4000
3000
2000
0
100
200
300
tcdh
vtyp
history
model


Peaks (3 Years) erc8d1.pgm
Weather Impact on Load (syear=2017, wyear=2017)
xvar
5500
5000
4500
4000
3500
3000
2500
2000
1500
1000
500
0
0
25
50
75
100
125
150
175
200
225
250
275
300
325
350
thdh
vtyp
history
model

The following table, Table 1, shows the maximum peak demand that would result from the most extreme weather since 1991. The table also shows the average peak demand which represents the peak demand expected under normal or average weather conditions today. Finally, the table shows the maximum deviation from normal that could occur on DESC's system due to abnormal weather. The results in Table 1 are for the regression models that are based on all the days in the season where degree hours were positive. The results suggest that the summer demand risk is 245 MW while the winter demand risk is 557 MW.

Table 1

MW Peak Demand				
Weather	**Maximum**	**Normal**	**Deviation**	**%Deviation**
Summer	**5,008**	**4,763**	**245**	**5.1%**
Winter	**5,412**	**4,855**	**557**	**11.5%**

Table 1a shows the results for the two alternate summer models, one quadratic and one linear, and both based on the 100 hottest days in the season. The demand risk based on the quadratic model is 281 MW while for the linear model the demand risk is 263 MW. The stepwise procedure chose the linear formulation of the model while stepwise was forced to estimate the quadratic formulation.

Table 1a

Summer Models Results Using 100 Hottest Days MW Peak Demand				
Weather	**Maximum**	**Normal**	**Deviation**	**%Deviation**
Summer Quadratic	**5,050**	**4,769**	**281**	**5.9%**
Summer Linear	**5,032**	**4,768**	**263**	**5.5%**

Similar data is presented in Table 1b for the two alternate winter models, again both based on the 100 coldest days in the season. The demand risk based on the quadratic model is 615 MW while for the linear model the demand risk is 507 MW. The stepwise procedure chose the quadratic formulation of the model while stepwise was forced to estimate the linear formulation.

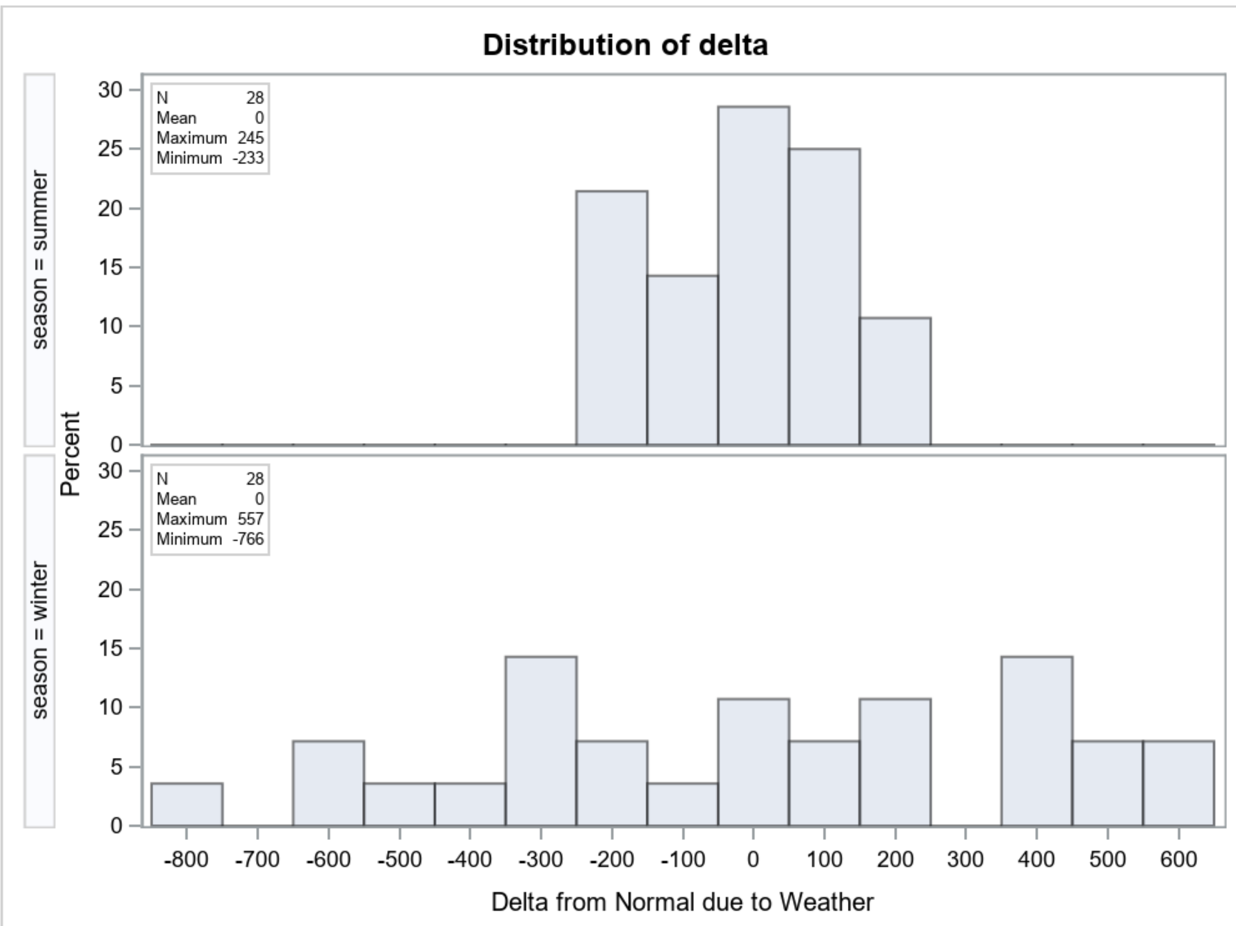
Table 1b

Winter Models Results Using 100 Coldest Days MW Peak Demand				
Weather	**Maximum**	**Normal**	**Deviation**	**%Deviation**

Winter Quadratic	**5,479**	**4,864**	**615**	**12.6%**
Winter Linear	**5,287**	**4,780**	**507**	**10.6%**

There are thus three estimates of demand side risk for the summer, i.e. the base level of 245 MWs and the two alternate estimates of 281 MW and 263 MW. For the winter season the base estimate is 557 MW while the two alternates are 615 MW and 507 MW.

The following chart shows the distribution of deviations about the mean using the quadratic model based on all days in the season. The top distribution for the summer period is similar to a normal or bell-shaped probability distribution while the bottom chart representing the weather risk in the winter is more spread out and similar to a uniform probability distribution.



The following table, Table 2, summarizes the risk of higher peak demands based on these distributions.

Table 2

MW Weather Deviations by Percentile				
Percentile	**75%**	**90%**	**95%**	**100%**
Summer	**118**	**173**	**214**	**245**
Winter	**380**	**531**	**554**	**557**

Clearly, winter weather poses a greater demand-side reliability risk than summer since the maximum deviation from a normal weather forecast can reach as much as 557 MW while in summer the maximum deviation is closer to 245 MW.

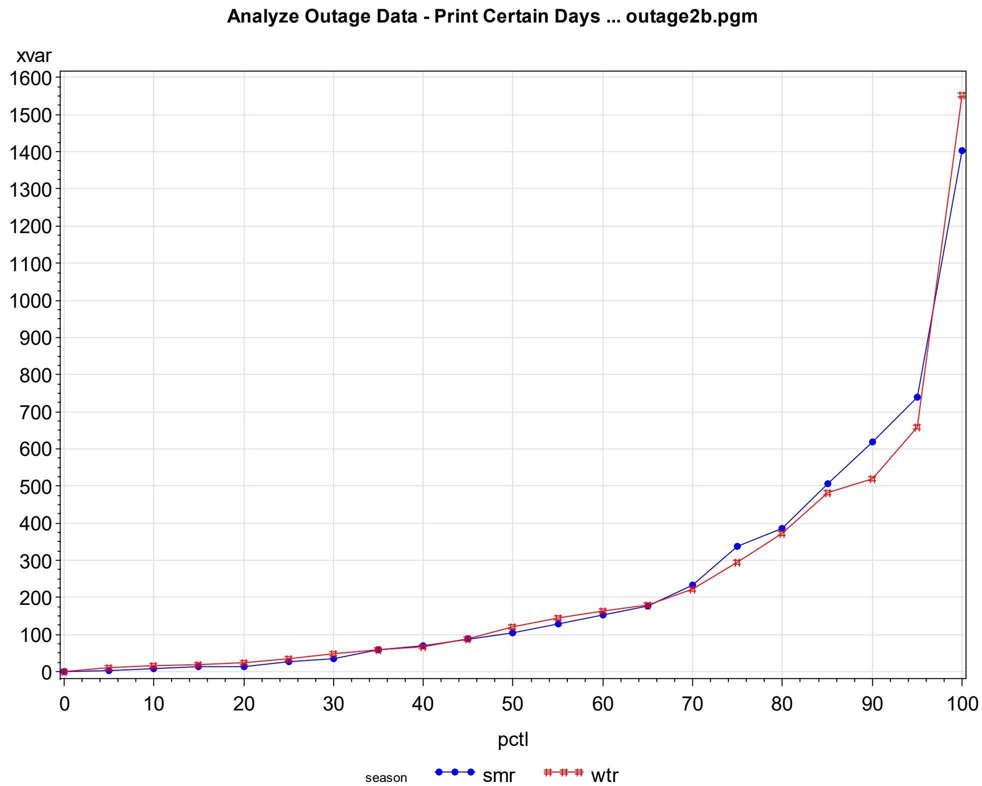
Supply-Side Risk

To quantify the supply-side risk, the forced outage history of DESC's generating units was analyzed. By calculating the number of MWs of generation that was forced out or de-rated on each day of the summer and winter, a distribution of outage was developed for the summer season and for the winter season. For summer, the daily outages during the months of June, July and August were studied for the years 2010-2017. For winter, the months of December, January and February were used. The resulting number of days used for summer and for winter was greater than 700 each season. Table 3 below summarizes each of these distributions of forced outages. For example, in summer it would take 234 MW of reserve capacity to replace the capacity forced out over 70% of the summer days being studied.

Table 3

MW Forced Out by Percentile						
Percentile	**50%**	**60%**	**70%**	**80%**	**90%**	**100%**
Summer	**106**	**152**	**234**	**385**	**618**	**1,402**
Winter	**121**	**165**	**223**	**373**	**520**	**1,552**

The following is the distribution in graphical form showing the accumulated MW out by the percentile in the probability distribution.



To maintain reliability and replace the loss of generating capacity up to 70% of the days in the winter, DESC estimates that it needs about 223 MW of reserve capacity.

<u>Summary: Reserve Capacity for Summer and Winter Peak Periods</u>

To calculate the required reserve margins for summer and winter peak periods, DESC used the maximum deviation from normal estimated in the demand-side risk analysis and the 70% cutoff value from the outage distributions developed for the summer and winter seasons. The following table summarizes the results.

Table 4

Reserve Margin for Summer and Winter Peak Periods		
	Summer	Winter
VACAR Operating	200	200
Demand-Side Risk	245	557
Supply-Side Risk	234	223
Total Reserve MWs	679	980
Normal Peak Demand	4,763	4,855
Reserve Margin %	14.3%	20.2%
Reserve Margin Policy	14%	21%

DESC's reserve margin policy is to have a level of capacity reserves at least as great as 14% of the normal weather summer peak forecast for the summer season and 21% of the normal weather winter peak forecast for the winter season.

<u>Base Reserve Capacity Needed to Operate the System Reliably Throughout the Year</u>

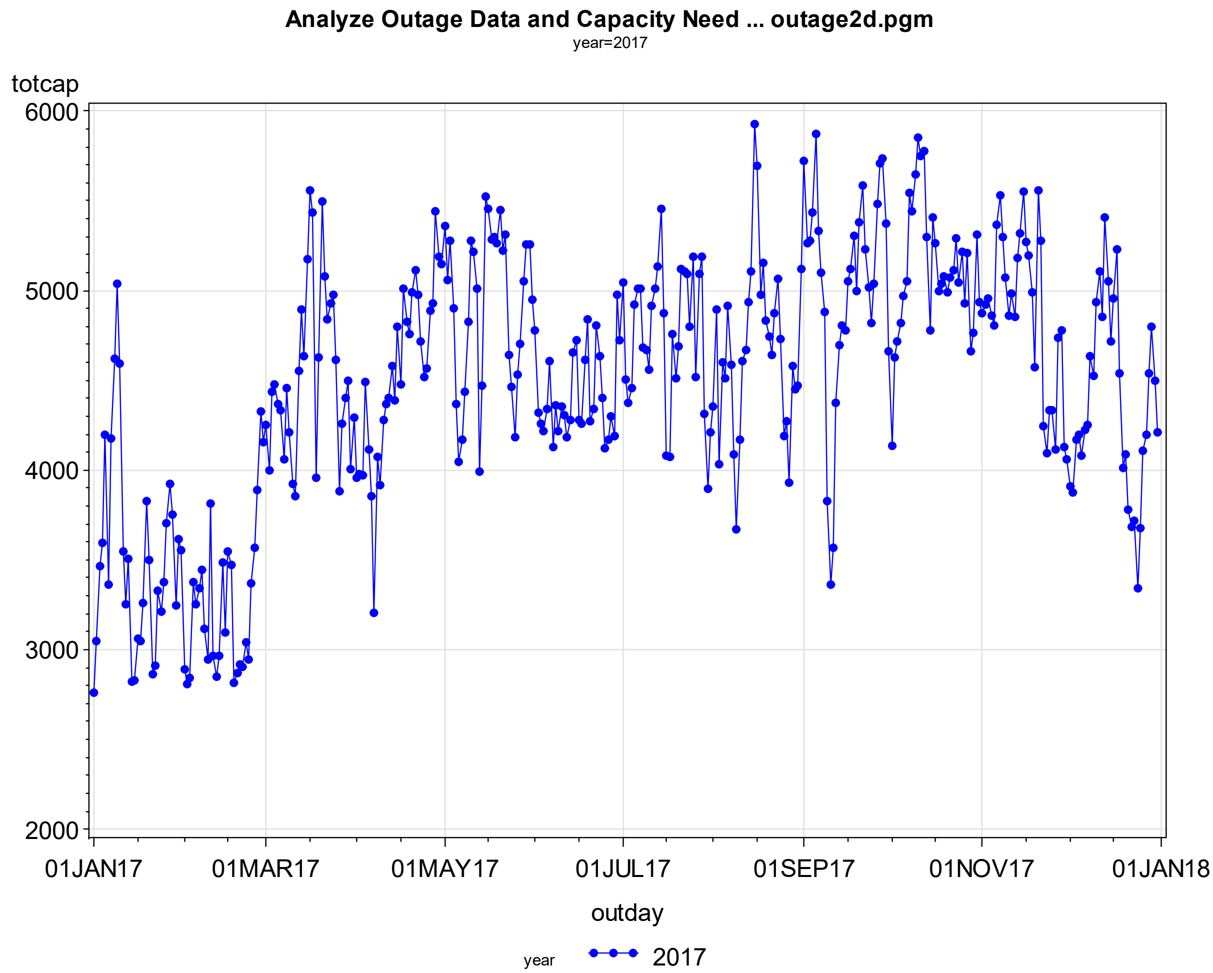
In addition to the reserves needed to address risk during the summer and winter peak periods, DESC needs a portion of this reserve capacity to operate the system throughout the year, not only to meet the load, but also to cover both scheduled and un-scheduled generating unit outages. To quantify this need DESC analyzed its forced and scheduled outages since 2010 and determined the capacity needed each day throughout the year. The basic formula relating available capacity and system need is the following.

$$\textbf{Total Capacity} - \textbf{MW Forced Out} - \textbf{MW Scheduled Out} = \textbf{Peak Load} + \textbf{Residual Operating Reserves}$$

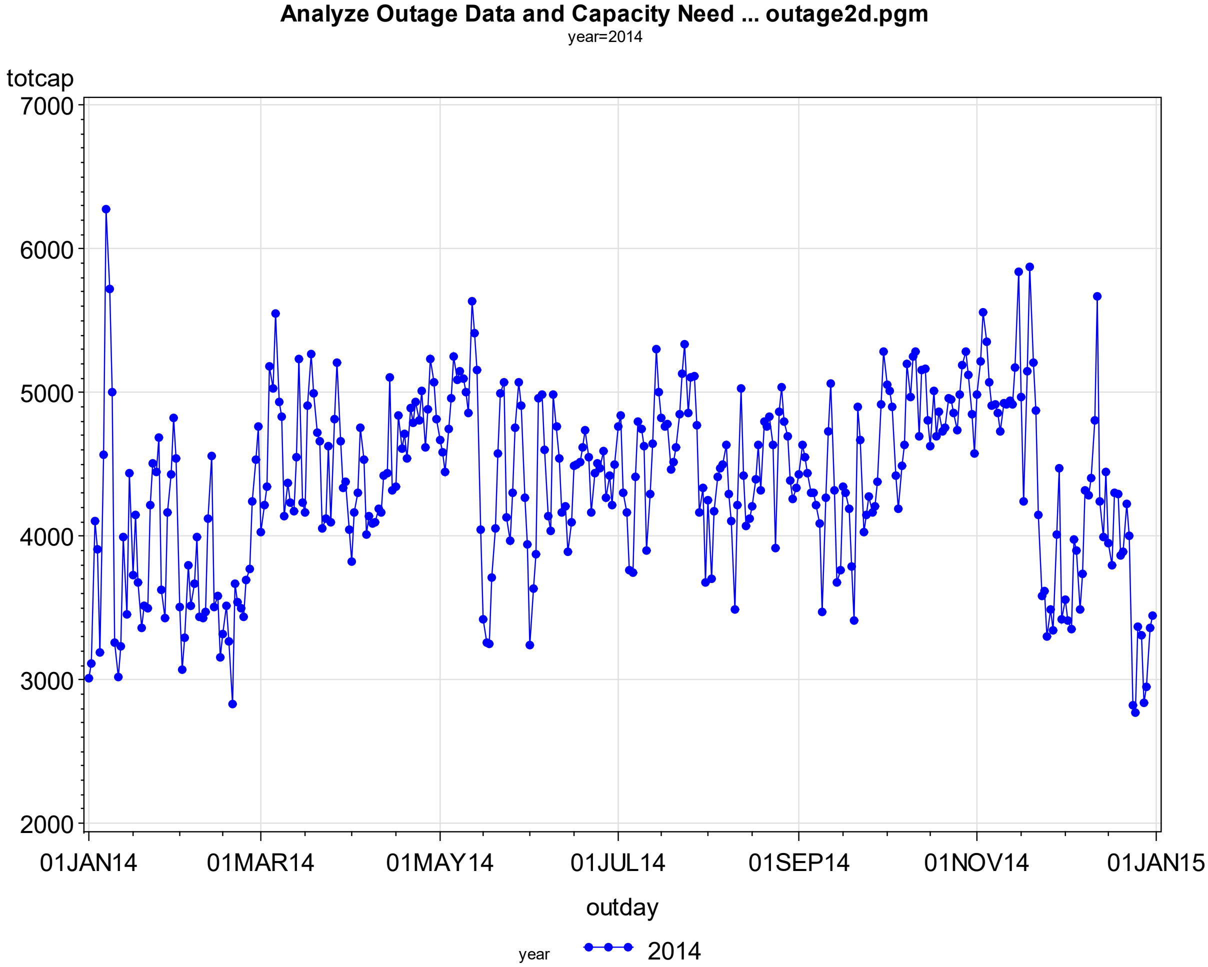
By rearranging terms, the daily capacity need can be calculated with this formula.

$$\textbf{Total Daily Capacity Needed} = \textbf{Daily Peak Load} + \textbf{MW Forced Out} + \textbf{MW Scheduled Out} + \textbf{Desired Daily Reserves}$$

Setting the "Desired Daily Reserves" equal to the VACAR Operating Reserve requirement which is about 200 MW, DESC can calculate its daily capacity need by using its historical experience with scheduled and forced outages. Following is a graph of the daily capacity need in 2017.



Below is the chart for 2014 which was the year when an arctic blast of cold air hit the southeast on January 7, 2014. The spike in capacity needed above 6,000 MW was principally caused by the forced outage of Williams Station on that day.



The daily capacity need for each year from 2010 to 2017 was calculated by season. Each year and season were considered a separate distribution of daily need and from each distribution the 95th, 96th, and 97th percentiles were extracted. These percentiles represented the amount of capacity needed to serve 95%, 96%, and 97% of the days in the distribution respectively. The peak days in the distribution, defined as the top 10 to 20 days of highest capacity need, correspond to a demarcation at the 95th and 97th percentile i.e. 10/365 is about 3% and 20/365 is about 5% of the days in the year or stated differently 355/365 is about 97% and 345/365 is about 95%. The individual years and seasons are shown in Appendix C in tabular form. The table below shows the average of these percentiles from the seven years studied. For example, in the summer, DESC needs about 5,309 MW of capacity to serve 95% of the days in the summer period while 5,406 MW is needed to serve 97% of the days in the winter period. Since this level of capacity is needed to serve most of the days of the year, DESC considers this a base level of capacity.

Table 5

Distribution of Daily Capacity Need at Certain Percentiles (MW)				
Percentile	**95%**	**96%**	**97%**	**100%**
Summer	**5,309**	**5,359**	**5,406**	**5,735**
Winter	**5,148**	**5,217**	**5,333**	**5,723**

In the following table, the base level of capacity is expressed as a percentage of the average maximum customer load occurring in the particular season. Averaging the percentages for the 95th and the 97th percentile yields 13.40% for summer and 14.95% for winter. DESC believes these results support the existing base reserve capacity need in summer of 12% of summer peak demand and in winter, 14% of winter peak demand.

Table 6

Daily Capacity Need Percentiles as Percent of Peak Load				
Percentile	**95%**	**96%**	**97%**	**100%**
Summer	**12.4**	**13.5**	**14.4**	**21.4**
Winter	**12.9**	**14.4**	**17.0**	**25.6**

<u>Conclusion</u>

For the summer months which include May through October, DESC requires base reserves in the amount of 12% of the summer peak load to operate the system reliably and 14% of summer peak load during the peak load periods. For the winter months of November through April, DESC requires 14% of the winter peak load forecast in base reserves to operate the system reliably and 21% for the peak load periods. The following table summarizes DESC's reserve margin policy.

Table 7

DESC's Reserve Margin Policy		
	Summer	**Winter**
Base Reserves	**12%**	**14%**
Peaking Reserves	**14%**	**21%**
Increment for Peaking	**2%**	**7%**

APPENDICES

Appendix A1- Stepwise Selection Results for Best Model in the Summer Season

Following is the SAS programming code showing the variables used in the stepwise variable selection process that identified the best regression model to use. The first set of SAS results are based on all days in the summer season while the second set is restricted to the 100 hottest days in the season.

```
proc reg;
model mxload=ihol wkend cdh cdh2 ysmr16-ysmr18
             yrlag1 yrlag2 imo6-imo8 idow1-idow7
   /slstay=0.15 slentry=0.15 selection=stepwise ss2 sse aic
```

All variables left in the model are significant at the 0.1500 level.

No other variable met the 0.1500 significance level for entry into the model.

Summary of Stepwise Selection

Step	Variable Entered	Variable Removed	Number Vars In	Partial R-Square	Model R-Square	C(p)	F Value	Pr > F
1	cdh		1	0.8106	0.8106	408.727	1172.53	<.0001
2	wkend		2	0.0754	0.8860	139.715	180.58	<.0001
3	imo6		3	0.0081	0.8941	112.642	20.77	<.0001
4	ihol		4	0.0079	0.9020	86.3367	21.77	<.0001
5	yrlag1		5	0.0061	0.9081	66.3849	17.94	<.0001
6	yrlag2		6	0.0120	0.9200	25.3887	40.25	<.0001
7	cdh2		7	0.0042	0.9242	12.4056	14.74	0.0002
8	idow6		8	0.0018	0.9260	8.1142	6.31	0.0126

Summary of Stepwise Selection

Step	Variable Entered	Variable Removed	Number Vars In	Partial R-Square	Model R-Square	C(p)	F Value	Pr > F
1	wkend		1	0.4893	0.4893	117.146	93.89	<.0001
2	cdh		2	0.1498	0.6391	56.6319	40.26	<.0001
3	yrlag1		3	0.0445	0.6836	40.0563	13.50	0.0004
4	imo8		4	0.0454	0.7289	23.1271	15.90	0.0001
5	ihol		5	0.0285	0.7575	13.2266	11.05	0.0013
6	yrlag2		6	0.0202	0.7776	6.8010	8.44	0.0046
7	idow2		7	0.0099	0.7875	4.6875	4.27	0.0417
8	idow6		8	0.0051	0.7926	4.5710	2.22	0.1393

Appendix A2

Best Regression Equation for Daily Summer Peak Demand Using All Days in the Season

Peaks (3 Years) erc8d1.pgm
Weather Impact on Load (syear=2017, wyear=2017)

The REG Procedure
Model: MODEL1
Dependent Variable: mxload

Number of Observations Read	304
Number of Observations Used	276
Number of Observations with Missing Values	28

Weight: wgts Weight

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	8	36958412	4619801	440.80	<.0001
Error	267	2798296	10481		
Corrected Total	275	39756708			

Root MSE	102.37437	R-Square	0.9296
Dependent Mean	4116.35770	Adj R-Sq	0.9275
Coeff Var	2.48701		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	4314.05871	13.82104	312.14	<.0001	0
ihol	1	-309.29412	59.87563	-5.17	<.0001	1.01487
wkend	1	-252.57647	14.42786	-17.51	<.0001	1.09179
cdh	1	8.87928	0.17995	49.34	<.0001	1.40974
cdh2	1	-1.04225	0.25947	-4.02	<.0001	1.15437
yrlag1	1	-127.38431	16.87435	-7.55	<.0001	1.63914
yrlag2	1	-106.65340	15.91125	-6.70	<.0001	1.45026
imo6	1	-70.01001	13.60334	-5.15	<.0001	1.05026
idow6	1	-44.79588	18.42714	-2.43	0.0157	1.07727

Appendix A3

Best Regression Equation for Daily Summer Peak Demand Using 100 Hottest Days

The REG Procedure
Model: MODEL1
Dependent Variable: mxload

Number of Observations Read	128
Number of Observations Used	100
Number of Observations with Missing Values	28

Weight: wgts Weight

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	8	2455308	306913	45.59	<.0001
Error	91	612658	6732.50611		
Corrected Total	99	3067966			

Root MSE	82.05185	R-Square	0.8003
Dependent Mean	4467.63602	Adj R-Sq	0.7827
Coeff Var	1.83658		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	4648.20040	26.45062	175.73	<.0001	0
ihol	1	-370.08203	87.21437	-4.24	<.0001	1.11836
wkend	1	-257.10638	19.35973	-13.28	<.0001	1.20227
cdh	1	5.53220	0.52673	10.50	<.0001	1.20077
yrlag1	1	-150.32611	26.49727	-5.67	<.0001	2.57565
yrlag2	1	-98.96052	28.16068	-3.51	0.0007	2.68500
imo8	1	76.64939	21.93000	3.50	0.0007	1.16996
idow2	1	53.61484	29.20818	1.84	0.0697	1.22061
idow6	1	-40.60254	26.45846	-1.53	0.1284	1.16455

Appendix A4

Forced Quadratic Regression Equation for Daily Summer Peak Using 100 Hottest Days

The REG Procedure
Model: MODEL1
Dependent Variable: mxload

Number of Observations Read	128
Number of Observations Used	100
Number of Observations with Missing Values	28

Weight: wgts Weight

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	9	2454427	272714	40.27	<.0001
Error	90	609423	6771.36156		
Corrected Total	99	3063849			

Root MSE	82.28828	R-Square	0.8011
Dependent Mean	4467.75253	Adj R-Sq	0.7812
Coeff Var	1.84183		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	4643.57818	28.83853	161.02	<.0001	0
cdh2	1	1.20883	2.97428	0.41	0.6854	1.37120
ihol	1	-370.91631	87.48302	-4.24	<.0001	1.11879
wkend	1	-256.31239	19.47177	-13.16	<.0001	1.20784
cdh	1	5.42183	0.59562	9.10	<.0001	1.52292
yrlag1	1	-149.59515	26.61498	-5.62	<.0001	2.58156
yrlag2	1	-98.26535	28.29569	-3.47	0.0008	2.69364
imo8	1	77.17477	22.06770	3.50	0.0007	1.17812
idow2	1	55.78299	29.63441	1.88	0.0630	1.24648
idow6	1	-41.00131	26.54183	-1.54	0.1259	1.16556

Appendix B1- Stepwise Selection Results for Best Model in the Winter Season

Following is the SAS programming code showing the variables used in the stepwise variable selection process that identified the best regression model to use. The first set of SAS results are based on all days in the winter season while the second set is restricted to the 100 coldest days in the season.

```
proc reg;
model mxload=wtr18 wtr17 wtr16 ihol wkend hdh hdh2
             yrlag1 yrlag2 imo1 imo2 imo3 idow1-idow7
   /slstay=0.15 slentry=0.15 selection=stepwise ss2 sse aic;
```

Summary of Stepwise Selection

Step	Variable Entered	Variable Removed	Number Vars In	Partial R-Square	Model R-Square	C(p)	F Value	Pr > F
1	hdh		1	0.8352	0.8352	499.083	1120.02	<.0001
2	wkend		2	0.0725	0.9077	185.158	172.83	<.0001
3	hdh2		3	0.0219	0.9296	91.8689	68.00	<.0001
4	yrlag1		4	0.0056	0.9352	69.5652	18.75	<.0001
5	ihol		5	0.0041	0.9392	53.8523	14.51	0.0002
6	imo1		6	0.0040	0.9432	38.5769	15.07	0.0001
7	imo2		7	0.0041	0.9472	22.9237	16.51	<.0001
8	wtr18		8	0.0032	0.9504	11.0415	13.75	0.0003
9	yrlag2		9	0.0011	0.9515	8.2156	4.87	0.0284
10	idow3		10	0.0006	0.9521	7.5592	2.70	0.1018

Summary of Stepwise Selection

Step	Variable Entered	Variable Removed	Number Vars In	Partial R-Square	Model R-Square	C(p)	F Value	Pr > F
1	hdh		1	0.7535	0.7535	208.026	299.51	<.0001
2	wkend		2	0.1388	0.8923	38.8423	125.00	<.0001
3	imo1		3	0.0067	0.8990	32.5593	6.38	0.0132
4	imo2		4	0.0061	0.9051	27.0918	6.06	0.0156
5	wtr18		5	0.0040	0.9091	24.1240	4.16	0.0441
6	ihol		6	0.0042	0.9132	20.9896	4.46	0.0373
7	idow4		7	0.0031	0.9164	19.1053	3.47	0.0658
8	idow5		8	0.0034	0.9198	16.8775	3.89	0.0516
9	yrlag2		9	0.0030	0.9228	15.1836	3.49	0.0649
10	yrlag1		10	0.0053	0.9281	10.6234	6.59	0.0119
11	hdh2		11	0.0019	0.9300	10.2847	2.39	0.1261

Appendix B2

Best Regression Equation for Daily Winter Peak Demand Using All Days in the Season

The REG Procedure
Model: MODEL1
Dependent Variable: mxload

Number of Observations Read	251
Number of Observations Used	223
Number of Observations with Missing Values	28

Weight: wgts Weight

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	10	81909963	8190996	595.95	<.0001
Error	212	2913832	13744		
Corrected Total	222	84823795			

Root MSE	117.23690	R-Square	0.9656
Dependent Mean	3070.04496	Adj R-Sq	0.9640
Coeff Var	3.81874		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	3081.98070	21.28983	144.76	<.0001	0
wtr18	1	-317.39459	73.15175	-4.34	<.0001	1.45162
ihol	1	-239.28587	46.98591	-5.09	<.0001	1.05933
wkend	1	-384.52527	18.84459	-20.41	<.0001	1.13403
hdh	1	7.20985	0.11521	62.58	<.0001	1.29567
hdh2	1	1.38666	0.13897	9.98	<.0001	1.38692
yrlag1	1	-119.31921	20.39391	-5.85	<.0001	1.44571
yrlag2	1	-59.78449	20.64403	-2.90	0.0042	1.43087
imo1	1	149.48924	20.49375	7.29	<.0001	1.52323
imo2	1	120.61541	20.99672	5.74	<.0001	1.43228
idow3	1	-25.30521	24.19476	-1.05	0.2968	1.09032

Appendix B3

Best Regression Equation for Daily Winter Peak Demand Using 100 Coldest Days

The REG Procedure
Model: MODEL1
Dependent Variable: mxload

Number of Observations Read	128
Number of Observations Used	100
Number of Observations with Missing Values	28

Weight: wgts Weight

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	11	21548692	1958972	119.11	<.0001
Error	88	1447294	16447		
Corrected Total	99	22995987			

Root MSE	128.24401	R-Square	0.9371
Dependent Mean	3622.51063	Adj R-Sq	0.9292
Coeff Var	3.54020		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	3661.10370	37.71154	97.08	<.0001	0
wtr18	1	-352.95242	98.25858	-3.59	0.0005	2.25146
ihol	1	-126.29951	84.64645	-1.49	0.1393	1.12477
wkend	1	-356.03305	30.91028	-11.52	<.0001	1.24642
hdh	1	9.34674	0.40978	22.81	<.0001	1.85395
hdh2	1	1.31612	0.83982	1.57	0.1207	2.97513
yrlag1	1	-104.40343	36.45048	-2.86	0.0052	1.47539
yrlag2	1	-91.83275	33.57892	-2.73	0.0075	1.55737
imo1	1	151.56425	35.40637	4.28	<.0001	1.84946
imo2	1	135.70447	39.17886	3.46	0.0008	1.61596
idow4	1	128.12104	46.58753	2.75	0.0072	1.18382
idow5	1	72.76690	43.05712	1.69	0.0946	1.18558

Appendix B4

Forced Linear Regression Equation for Daily Winter Peak Using 100 Coldest Days

Peaks (3 Years) erc8d1.pgm
Weather Impact on Load (syear=2017, wyear=2017)

The REG Procedure
Model: MODEL1
Dependent Variable: mxload

Number of Observations Read	128
Number of Observations Used	100
Number of Observations with Missing Values	28

Weight: wgts Weight

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	10	21630957	2163096	137.39	<.0001
Error	89	1401264	15745		
Corrected Total	99	23032221			

Root MSE	125.47723	R-Square	0.9392
Dependent Mean	3622.83771	Adj R-Sq	0.9323
Coeff Var	3.46351		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	3683.49549	34.38143	107.14	<.0001	0
wtr18	1	-265.97943	76.53139	-3.48	0.0008	1.42695
ihol	1	-463.11021	129.08845	-3.59	0.0005	1.04753
wkend	1	-357.38178	29.85925	-11.97	<.0001	1.21722
hdh	1	9.63809	0.37173	25.93	<.0001	1.59300
yrlag1	1	-102.01486	35.49664	-2.87	0.0051	1.46661
yrlag2	1	-110.16577	32.27602	-3.41	0.0010	1.50360
imo1	1	161.91774	33.47049	4.84	<.0001	1.73247
imo2	1	137.88242	38.29822	3.60	0.0005	1.60778
idow4	1	117.78909	44.56174	2.64	0.0097	1.13181
idow5	1	71.81312	41.87812	1.71	0.0899	1.17208

Appendix C:

Daily Capacity Need by Year and Season for Certain Percentiles in the Distribution

Analyze Outage Data and Capacity Need ... outage2d.pgm

seas	wyear	ndys	mxcap	mxload	cap95	cap96	cap97	mxresm	mxresm 95	mxresm 96	mxresm 97
summer	2010.0	184.0	5778.0	4735.0	5268.0	5322.0	5418.0	22.0	11.3	12.4	14.4
	2011.0	184.0	5697.5	4885.0	5418.5	5470.0	5492.0	16.6	10.9	12.0	12.4
	2012.0	184.0	6181.5	4761.0	5224.5	5256.5	5299.5	29.8	9.7	10.4	11.3
	2013.0	184.0	5645.0	4574.0	5264.0	5306.0	5392.5	23.4	15.1	16.0	17.9
	2014.0	184.0	5636.5	4594.0	5195.5	5254.5	5286.5	22.7	13.1	14.4	15.1
	2015.0	184.0	5386.0	4750.0	5115.0	5167.0	5197.5	13.4	7.7	8.8	9.4
	2016.0	184.0	5631.5	4807.0	5343.0	5393.5	5425.5	17.2	11.2	12.2	12.9
	2017.0	184.0	5927.5	4697.0	5646.5	5705.5	5734.5	26.2	20.2	21.5	22.1
summer		184.0	5735.4	4725.4	5309.4	5359.4	5405.8	21.4	12.4	13.5	14.4
winter	2010.0	181.0	5285.0	4718.0	5008.0	5049.0	5102.0	12.0	6.1	7.0	8.1
	2011.0	181.0	5641.5	4868.0	5017.5	5043.0	5135.0	15.9	3.1	3.6	5.5
	2012.0	182.0	5832.5	4397.0	5316.0	5379.0	5426.5	32.6	20.9	22.3	23.4
	2013.0	181.0	5958.5	3984.0	4920.5	5078.0	5389.5	49.6	23.5	27.5	35.3
	2014.0	181.0	6272.5	4853.0	5235.0	5349.5	5560.5	29.2	7.9	10.2	14.6
	2015.0	181.0	5601.5	4970.0	5082.0	5116.5	5251.5	12.7	2.3	2.9	5.7
	2016.0	182.0	5632.0	4409.0	5286.5	5315.5	5357.0	27.7	19.9	20.6	21.5
	2017.0	181.0	5561.0	4457.0	5316.0	5406.0	5442.5	24.8	19.3	21.3	22.1
winter		181.3	5723.1	4582.0	5147.7	5217.1	5333.1	25.6	12.9	14.4	17.0